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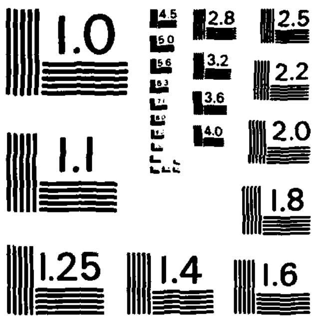

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THE APPLICATION OF A TECHNOLOGY INDEX
TO AIRCRAFT TURBINE ENGINE
COST ESTIMATING RELATIONSHIPS

THESIS

Wendell P. Simpson III   James R. Sims Jr
Captain, USAF   Captain, USAF

AFIT/GSM/LSY/84S-25

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The contents of the document are technically accurate, and no sensitive items, detrimental ideas, or deleterious information are contained therein. Furthermore, the views expressed in the document are those of the authors and do not necessarily reflect the views of the School of Systems and Logistics, the Air University, the United States Air Force, or the Department of Defense.

forecasting field has been applied to try to improve the estimating properties of a CER. The results of the application are a significant and valid cost driver for the use in a CER.

We would like to express our appreciation to a number of individuals whose efforts have made this project possible. Dr. Joseph P. Martino shared with us his tremendous insight into the field of technological forecasting. Without his help, we would still be at the starting line. Dr. Theodore J. Gordon provided key assistance and recommendations about the application of his technology measurement technigue. Mr. John Birkler supplied the data that was critical to this study. As our thesis advisor, Mr. Richard L. Murphy provided invaluable advice and guidance in times of need. Finally, a special thanks go to Emilie and Lisa who supplied the support, motivation and consolation that are so important to the successful completion of a thesis effort.

Wendell P. Simpson III

James R. Sims Jr.

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Notation

CER	Cost Estimating Relationship.
MACH	Maximum flight envelope Mach number (measure speed relative to the speed of sound); 1.0 for subsonic flight engines.
MQT	Model Qualification Test.
MQTCOST	Development cost to MQT.
PROCOST	Cumulative average production cost through the 1000th engine.
QTY	Quantity of engines produced.
SFC	Specific fuel consumption at military thrust, sea-level static conditions (lb/hr/lb thrust).
SOA	State-of-the-art index.
SOAH	State-of-the-art index derived from the hyperbolic tangent curve.
SOAL	State-of-the-art index derived from the linear model.
TOA	Time of Arrival at successful MQT (measured in calendar quarters since the third quarter of 1942).
THR	Maximum rated thrust at sea-level static conditions, including afterburner thrust if any (lb).
TTW	Thrust-to-weight ratio.
TIT	Turbine inlet temperature (degrees Rankine).
TDEVCOST	Total cost of development including development to MQT and product improvement.

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Abstract

Technological change may affect a cost estimating relationship (CER) by either changing the functional relationship between the dependent variable (cost) and the independent variables (cost drivers), or by changing the values of the parameters in the equation, or bo[illegible] In order to account for the impact of technologic[illegible] change, the impact must be quantified in some way and [illegible] quantification incorporated into the CER. One approach which has been tried is to introduce a variable which is "technologically driven". This variable, which should respond in a stable and predictable manner to any technological change, could function as a proxy measure for actual technological change. The problem is that all cost drivers react to some degree from technological change, and all cost drivers change for reasons other than changing technology. The use of a proxy variable is imperfect, at best.

This research attempts to develop a technological index, based on selected characteristics of new products, which measures the state-of-the-art at the point in time when each product was being developed. The methodology

employed to develop the index was adopted from the technological forecasting community, where it is accepted as a valid technique for quantifying technological change. Several indices were developed to measure the level of technology incorporated into the design and development of aircraft turbine engines. Each index was based on a different assumption about the expected time path of technological growth. The data set was restricted to the same engines used by Rand to develop a set of CERs for estimating the development cost to MQT, producion cost, and the total development cost of jet engines. Selected indices were then introduced into the Rand CERs to evaluate their impact as cost drivers and their relationship to the other variables in the equations. The application resulted in the technology indices being significant and valid cost drivers.

THE APPLICATION OF A TECHNOLOGY INDEX TO AIRCRAFT TURBINE ENGINE COST ESTIMATING RELATIONSHIPS

I. Introduction

Background

The Department of Defense (DoD) has three basic techniques for estimating new weapon system costs: the specific analogy, the engineering (grassroots) method, and the parametric estimating method. The specific analogy equates a known cost of an item to a similar item in a new system to achieve an estimate. This can be a useful technique especially when time is limited. A major disadvantage is that judgement must be relied on (22:71). The engineering method calls for building the estimate from the ground up, by estimating each component's probable cost and compiling the estimates into an overall system cost (27:12). As a result, this method requires detailed system definition, which is usually not available early in the system acquisition cycle. Another drawback of the engineering method is the enormous amount of time and manpower needed to produce a valid estimate.

Parametric cost estimating relationships (CERs) represent the most relied upon method of producing weapon

system cost estimates early in the program life (21:2). CERs are popular because they require small amounts of information, time, and manpower, yet produce reasonably accurate estimates of actual system cost. Parametric CERs are mathematic expressions that relate cost as a dependent variable to one or more independent variables. The independent variables are generally physical and/or performance characteristics (parameters) that describe the system and are referred to as cost drivers. Historical data are gathered on similar systems to the one being estimated, and multivariate regression is applied to determine the relationship between the independent variables and cost. The resulting model can then be used to predict the cost of new systems. The estimate is derived by simply inserting the expected values of the parameters for the new system as the independent variables in the CER.

Despite the widespread application of the CER technique in DoD, CERs do have shortcomings and have been the subject of recent criticism (12:v-1). Defense analysts have observed that prices paid for weapon systems have consistently exceeded the estimates derived from CERs (25:1). Two possible explanations for this situation are: the original cost estimate is too low, or the estimate is reasonable but the program is not adequately controlled (8:165). It is unlikely that the cause of cost overruns lies in either one or the other of these explanations: it

is most likely attributable to a combination of under estimation and inadequate program control. In any event, this research effort assumes that part of the observed difference between estimated and actual costs is due to inaccuracies in the original cost estimates. A further assumption is that these inaccuracies are a direct result of deficiencies in CERs. More accurate estimates are needed to close the gap between DOD budgets and the actual prices paid for weapon systems.

Technology

Traditionally, the physical and/or performance characteristics of a system (i.e., airframe weight and aircraft speed) are used as the explanatory variables in a CER. A problem with this approach is that physical and performance characteristics make no direct accounting of the means used to achieve the system parameter values. In other words, the technology used in a system is not directly accounted for in traditional CERs. Experts theorize that the reason for the tendency of CERs to underestimate actual costs is in the inability of physical and performance characteristics to capture the total cost impact of advances in the level of technology (21:4; 11:20; 27:15). As a result, the cost estimating community has continually strived for an explicit measure of the level of technology used in a weapon system (11:22). This measure would be used as an independent variable in a CER to

directly account for the cost impact of the level of technology. This research project is a continuation of that effort: to incorporate an explicit technology factor into a CER in the hope of improving estimating accuracy.

Before the relationship between the level of technology and the cost of a weapon system can be explored, a technique for quantifying technology is required. Technology is not a directly measurable quantity and a proxy measure is required (1:3). The cost estimating community has proposed several techniques for developing a technology proxy and these are reviewed in the next chapter. Ideally it is desirable for a technology proxy constructed for use in a CER to be derived from a technique that has the following characteristics:

1) the technique used to produce the proxy should be applicable to any system of interest.

2) the technique should produce results in the form of an index.

3) the technique should be objective in nature.

4) the technique should produce results that are consistent with subjective notions of the level of technology of the system.

These characteristics will function as the criteria for selecting the measurement technique to be used in this thesis effort.

Cost estimators are not the only ones interested in measuring technology. The technology forecasting community has investigated the nature of technology advance and has regularly reported the results in Technological Forecasting

and Social Change. This journal has been the showcase of the technology forecasting community for over a decade. Technology forecasting can be defined as "a quantified prediction of the timing and of character of the degree of change of technical parameters and attributes associated with the design, production, and use of devices, materials, and processes, according to a specified system of reasoning" (15:3). The technology forecasting community has proposed several methodologies for quantifying the level of technology of a given type of system.

One technique presented recently is a technology measurement convention developed by T.J. Gordon and T.R. Munson. This technique was described in the article "A Proposed Convention for Measuring the State-of-the-Art of Products and Processes," published in the October 1981 issue of Technological Forecasting and Social Change. The Gordon-Munson model meets the established criteria for a CER technology variable. The technique is applicable to any system of interest and produces a technology measure in the form of an index, which represents the relationship of the current state-of-the-art to a reference value (9:3). The Gordon-Munson technique allows for both subjective and objective methods of arriving at the index. In Gordon and Munson's article and in an ensuing article by Edwards and Gordon (4), the technique is applied to systems to test the validity of the measure against intuitive notions of technology advance. The results of the applications made

in these articles show that "changes in the measures correlated with innovations in the field" (4:153).

Problem

Gordon and Munson have proposed a technique for quantifying technology. This technique has been applied to systems and produced intuitively appealing results. The proxy the technique produces has characteristics that are desirable in a technology measure for use in a CER. Research, as presented in the next chapter, has revealed no applications of this technique to cost.

This discovery is not surprising, since there has been a marked lack of reference in the cost estimating literature to any work published in the technology forecasting journals. Of all the cost estimating literature reviewed, only one document makes any reference to the journal Technological Forecasting and Social Change. This apparent lack of dialogue was confirmed in conversations with Dr. J. P. Martino, an expert and prominent figure in the technology forecasting field (13). (Dr. Martino recently organized a seminar, sponsored by the National Science Foundation in Dayton, Ohio, and gathered together experts from both fields. One of the main purposes of the seminar was to improve the exchange of knowledge between the cost estimating and technology forecasting communities.) The application of techniques developed by the technology forecasting community may aid

the cost estimating community in their effort to develop a significant technology factor for application in cost estimating relationships. Gordon and Munson's model is one technology forecasting technique that provides an explicit technology measure that may improve cost estimating accuracy.

Research Objective

The objective of this research effort is to apply the technique developed by Gordon and Munson in an attempt to derive a measure for the level of technology used in a weapon system. The resulting index will then be incorporated in a CER that does not already include an explicit technology variable. The results will be analyzed to discover if the technology variable improves the estimating accuracy of the CER.

II. Literature Review

Introduction

The search for a technology factor for use in CERs has continued for over two decades. The efforts to develop such a factor are driven by the belief that estimating relationships based on physical and performance characteristics do not fully account for the costs of advancing technology. The premise of the previous studies is that an advance in the level of technology required by a system leads to a higher cost for the system. The term "technology" is not explicitly defined in the majority of past efforts. It is generally implied to mean the application of knowledge gained through pure research.

There are two distinct ways in which technology may affect system cost. The first involves the application of technology to the production process. This alters the production function, and is generally expected to decrease the cost of a system (25:35). New technology can also be applied to change the design of the system itself. The effect of this type of application can be to either increase or decrease costs. An improvement in the design of the system will tend to increase costs and vice versa (25:35).

While it is theoretically possible to distinguish between these two components of technological advance, it

is empirically difficult to resolve. This can be partially attributed to the unfortunate fact that technology is not a directly measurable quantity. Another consideration that clouds the distinction is the interdependent nature of the two components. For example, it is possible that the introduction of new production technology would pave the way for improvements in system quality. This rather ambiguous situation has resulted in attempts to create technology factors that explain the gross effect of technological advance. The one exception is Noah's 1973 Aircraft CER which is reviewed later in this chapter.

This chapter is a review of some of the more notable attempts to explicitly account for technological advance of systems in CERs. Given this scope, a search of the literature uncovered relatively few published efforts, and no books on the topic. The majority of the techniques reviewed are presented in reports either contracted for by the Department of Defense or written by DoD personnel. The literature search concentrated on, but was not restricted to, work done in estimating weapon system costs.

This review classifies technology factors as either judgmental or objective and presents them accordingly. Judgmental techniques are those that generate factor values that depend on the opinion of some group or individual. These are qualitative factors where no two independent observers can be expected to arrive at the same result or set of values. Objective factors are defined as those

developed independent of judgments or subjective evaluations. This group of techniques will result in an identical set of factors if the procedure is repeated by an independent observer.

Judgmental Technology Factors

One of the earliest attempts to incorporate a technology measure into cost estimating emerged in the early 1960's (26). The work centered around a technology factor developed by the Rand Corporation and was simply labeled "A". The "A" factor was defined as a descriptor of the magnitude of technological advance sought for a particular system. The factor was assigned a value ranging from zero to twenty, with the larger values representing systems requiring a higher level of technology. Robert Summers of the Rand Corporation used this technology factor in an empirical analysis of actual versus estimated costs of specified weapons systems (26). In this application, values for "A" were generated by surveying engineers from the Rand Corporation familiar with each particular system. The engineers were asked to "relate subjectively the magnitude of the improvement in the state of the art required for each of the development programs" (25:25). Summers combined the "A" factor with other variables to predict the ratio of actual to estimated costs (cost factor). Harman and Henrichsen (10) applied the "A" factor technique in their analysis of cost factors.

Another example of a judgmental technology factor is one developed for the Unmanned Spacecraft Cost Model (USCM) used at Space Division (AFSC) (7). The USCM accounts for the cost impact of technology in a rather unique way. Instead of incorporating a technology factor as an independent variable in the CERs, the USCM uses the factor to normalize the data base. The Technology Cost Carryover Factor (TCF) is based on the premise that engineering learning about unmanned spacecraft systems has occurred over time. This learning accumulates and is applied to successive systems. TCF "attempts to capture the cost impact of this previous knowledge" (7:V-2). TCFs are generated at the subsystem level, range from zero to one, and are based on the expert opinion of engineers in the unmanned spacecraft industry. The data base is normalized using a weighted sum of the TCF, a subjective complexity factor, and an "other" factor ("for those influences not related to either technology carryover of the complexity of design" (7:V-10)). When the normalization technique was applied, "the CERs generally showed statistical improvement" (7:V-16).

Objective Technology Factors

J.W. Noah and Associates, Inc., included an objective technology factor in aircraft CERs developed under contract to the Navy in 1972 (20). Noah had observed that "the dominant motivations in aircraft performance

improvement have generally been provided by <u>fighter</u> aircraft performance requirements" (20:30). As a result, Noah hypothesized that each new fighter aircraft model represented an advance of technology. He decided to "use the cumulative number of different fighter aircraft models (both experimental and production) as a proxy technology variable" (20:30). The technology index proved to be a statistically significant explanatory variable of both nonrecurring and recurring airframe costs. Also included in the airframe CERs was a judgmental complexity index dummy variable to adjust the CERs for aircraft systems that "had a major mission or performance parameter which required significantly new and complex technology" (20:48). Noah implied that the distinction between the technology and complexity indices lay in the ability of the technology index to account for advances in production technology, and the complexity index to capture advances in the technology of the actual system. The technology index in both airframe CERs, however, has a positive coefficient. This would suggest the production costs increase with each successive aircraft model, and this is counterintuitive to the popular belief that advances in production technology generally decrease production costs.

Avionics systems are possibly the most susceptible to advances in technology. In preliminary work on cause-effect relationships, Preidis (21) related ownership requirements of avionics systems to specific design

characteristics of the system. One such characteristic she employed was a technology index developed by William A. Falkenstein of LTV Aerospace Corporation. In the process of generating predictors of avionics weight and capability, Falkenstein (6) derived a "raw technology index" measuring the functional density of avionics system and showed a steady increase of the index over time. Preidis borrowed this index and paired it with a subjective complexity index to attain an avionics CER capable of predicting the unit cost of line replaceable units. The technology index also proved to be statistically significant in estimating relationships for Shop Replaceable Units per Function and Mean Time Between Defective Removals.

Alexander and Nelson (1) of the Rand Corporation have provided the most well-known and rigorous technique for developing a technology factor for a CER. Their measure was prompted by a requirement for a method that more objectively quantifies the technological state-of-the-art of a system (1:1). The technique was first presented in 1972, and is based on the theory that certain technical parameters that characterize a system should be indicative of the point in time that a system demonstrates a specified level of performance. The authors reasoned that an equation relating the parameters of a system and the date it achieves performance would constitute a technology index. Alexander and Nelson chose aircraft turbine engine systems to test their theory.

Turbine engine data was selected because "(1) qualitatively, a strong technological trend was evident over a thirty year period, (2) an adequate data base was available, and (3) turbine engines are important products incorporating billions of dollars of development and procurement resources" (1:11). The authors believed the Model Qualification Test (MQT) date best represented the point in time "that a level of technology was demonstrably available for production" (1:23). MQT is a series of tests, including a 150 hour endurance test, that an engine must pass before it can be produced. As a result, the MQT date was identified as the dependent variable and was measured in quarters beginning with the fourth quarter of 1942. Various combinations of performance and/or technical parameters were tested as independent variables using multivariate regression. (The distinguishing feature between technical (input) and performance (output) parameters is that "performance parameters give the device value to the user (thrust or weight, for example) and technical parameters make the performace parameters possible (turbine inlet temperature or overall pressure ratio). These two subsets are not independent and they may overlap to some extent" (1:4)). The equation selected as best representing a technology index for aircraft turbine engines was in semi-logarithmic form and contained one input and four output parameters. The signs of the coefficients for each variable were consistent with

intuitive notions of what constitutes technological advance; positive signs on coefficients where increased values of parameter indicate technological advance, and negative coefficients where decreases in parameter values are more highly valued. The choice of semi-logarithmic specification was based on the criterion of best statistical fit of the data.

Figure 1 is a plot of the technology index. The vertical axis is the value of the predicted MQT date and the horizontal axis is labeled with the actual date with the 45 degree line representing the expected values. "Points plotted above the 45 degree line represent engines ahead of their time: that is, their parameters, taken as a whole, appeared earlier than predicted by the equation. Likewise, points below the line are "late" or "conservative" developments" (1:25).

Alexander and Nelson's technology index was an innovative and promising breakthrough in the effort to develop a technology factor for use in CERs. In 1974, Nelson teamed up with F.S. Timson, also of the Rand Corporation, and attempted to apply this factor to aircraft turbine engine acquisition costs (18). Before doing so, however, the calculated MQT equation developed in the previous study was renamed Time of Arrival (TOA) and two explanatory variables in the equation were modified. Maximum thrust was substituted for military thrust and a pressure term replaced dynamic pressure. In addition, the

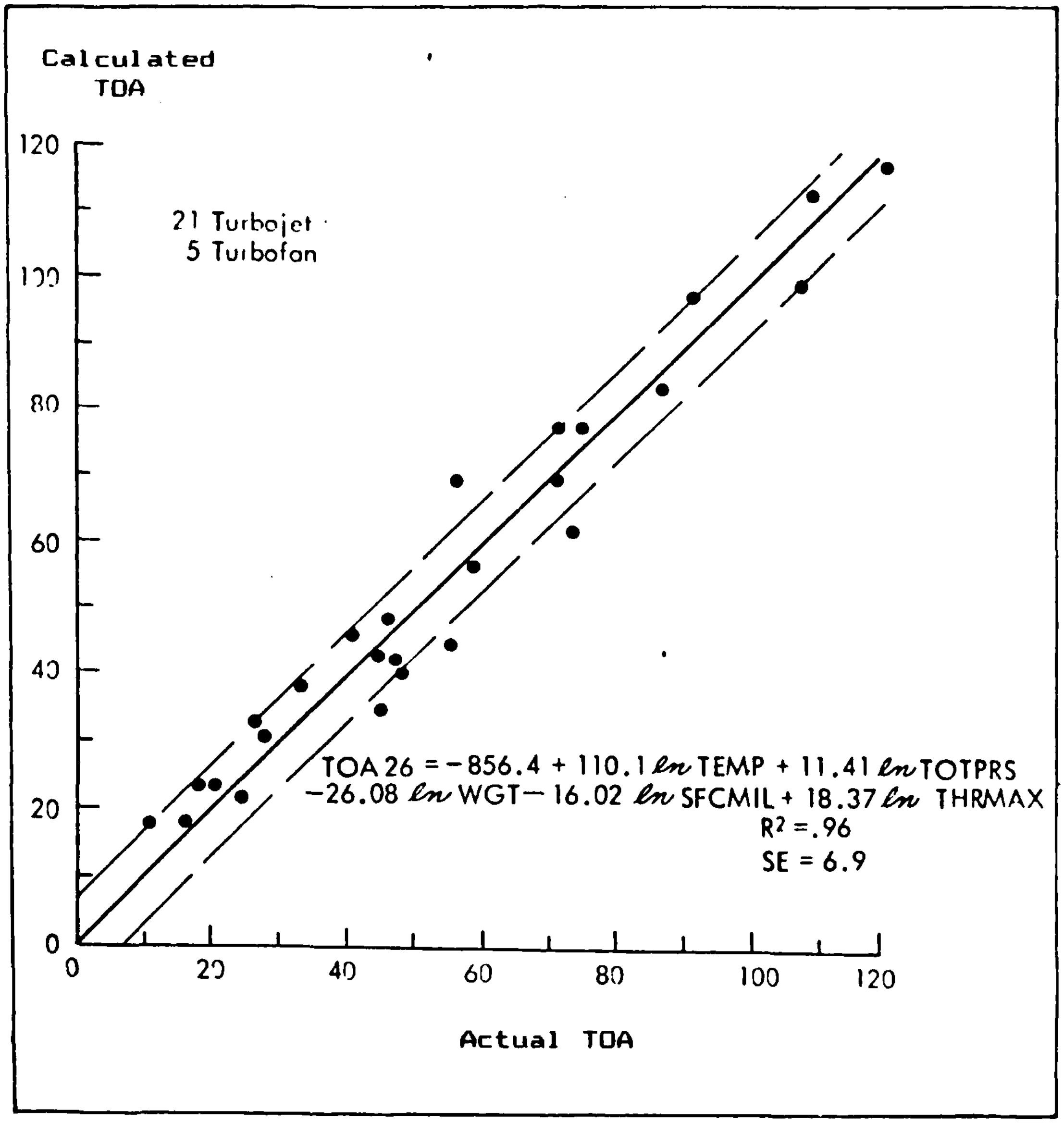

Fig. 1. Military Turbine Engine Time of Arrival

turboprop/turboshaft engines were deleted from the data due to insufficient development and production cost figures.

TOA and ΔTOA (the difference between the actual and expected dates that an engine successfully passes its MQT) were applied to four measures of production and development costs "with not completely satisfactory results" (11:24). The four measures of cost were: development cost to MQT, one-thousandth unit production cost, production unit progress slope, and total development cost.

Nelson and Timson's methodology called for the calculation of three equations for each of the four measures of cost. The "standard" variables equation regressed variables previously identified as important parameters against cost. The "time-of-arrival" equations combined standard variables with TOA, ΔTOA, or both. The "technology parameters" equations employed standard variables along with technology parameters found in the TOA equation. The stepwise least squares regression technique was used to develop all equations.

The time-of-arrival model made its best showing in the "development cost to MQT" equation. The TOA based model was also the best of the three equations for 1000th unit production cost, but the results were less clear-cut. The TOA model did not offer any advantages in predicting total development cost or production unit progress slope.

Nelson and Timson repeatedly emphasized that the TOA index "represents the time of arrival (150 hr MQT or

FAA Certification) of a demonstrated level of performance. This demonstrated performance is assumed to represent the best effort of the aircraft turbine engine industry; it thus is considered to be the technological state of the art of U.S. aircraft turbine engines" (18:13). In other words, the validity of the TOA measure hinges on the validity of the assumption of continual pressure to advance technology with resultant continual progress.

Since the work of Alexander and Nelson, the TOA factor has been applied in several efforts with varying degrees of success. In 1975, Nelson employed TOA as a measure of program risk and then explored the degree to which "you expose the engine to performance shortfall or to potential cost growth and schedule slippage by asking for it ahead of time rather than within a time schedule determined by the state of the art" (17:2-3). In 1977, Nelson expanded on his original analysis of engine costs to include life cycle costs (16). Stanley and Miller (24) developed an equation for first flight date of fighter aircraft using the TOA technique in 1979. However, their measure appeared totally uncorrelated to aircraft cost.

The latest chapter in the TOA technology factor was contained in a Rand study by Birkler, Garfinckle and Marks in 1982 (2). Their study updated the CERs for aircraft turbine engines originally developed by Nelson and Timson in 1974. In this study, TOA was relegated to the role of an independent measure of risk and not included as an

explanatory variable in the CERs. Birkler explained the exclusion as personal preference of the selection of independent variables.

Conclusions

The purpose of this thesis effort is to improve the estimating capability of a CER by incorporating an explicit measure of technology in the relationship. Previous attempts to accomplish this objective have been reviewed. Both subjective and objective techniques were presented. Neither type of technique is inherently superior to the other, but the emphasis over the recent past has been on objective techniques (23:2). The preference can be explained by the ability of others to replicate objective methods which permits a more valid analysis and critique of the resulting measures (15:16).

The Gordon and Munson convention, which was discussed in the last chapter, can be applied to objectively quantify the technology level of a weapon system. A search of the literature has not revealed any applications of this technique for the purpose of creating a technology variable to improve the estimating capability of a CER.

III. Methodology

Recently, a technique was proposed by T.J. Gordon and T.R. Munson (9) for calculating a technology index for a system. Their approach was published in the journal Technological Forecasting and Social Change and has since been applied to various system types (4). The applications indicate that the technique is capable of objectively quantifying technology for a broad range of system types, and that the resulting indices are consistent with respect to intuitive notions regarding the levels of technology within a system. A literature search has revealed that this technique has yet to be applied to derive an index for use as an explicit technology variable in a CER. The objective of this thesis is to apply the Gordon-Munson technique to a weapon system data base and produce an technology index for the system. The index will then be incorporated in a CER for that system. The results will be analyzed to assess the contribution of the variable to the explanatory capability of the CER.

The first section of this chapter will be a summary of the Gordon-Munson approach to quantifying technology. The second section will identify the system to be studied and will include a summary of the technological growth evident in the system, and a presentation of the baseline CERs and the data employed in this effort. The third

section will be a presentation of how the Gordon-Munson technique will be applied in this study to create technology indices. Finally, the fourth section will outline the methodology for assessing the contribution of the technology indices to the estimating relationships.

Gordon-Munson Technique

This section is a summary of the article "A Proposed Convention for Measuring the State of the Art of Products or Processes" by T.J. Gordon and T.R. Munson (9). The technique proposed by Gordon and Munson for quantifying technology can be represented by two models. The arithmetic model is:

$$SOA = K1(P1/P1') + K2(P2/P2') + \ldots + Kn(Pn/Pn') \quad [1]$$

where SOA = state of the art, n = the number of parameters, K = the relative weight assigned to each parameter, P = the value of the parameters determined to be meaningful in describing the state of the art, and P' = a reference value for that particular parameter. The alternative is the multiplicative model, and will be reviewed later in this section.

The first step in applying the model is selecting the parameters to be included. It is important that the purpose of the system be understood and that the parameters reflect the critical engineering goals of the design process. In other words, the parameters should be such that an increase in their value represents an advance of

the technology incorporated within that system. Physical, performance, and program parameters are all candidates for describing the technology of a system. All parameters should be formatted so that increasing values represent advances in the technology level of the system. This convention ensures that the weights will all be positive quantities.

The reference values, P′, are used to normalize the parameters. Normalizing the parameters makes SOA a dimensionless number so as to "facilitate comparison between and among technologies" (9:4). Gordon and Munson list several possibilities, of which some are; the maximum observed value in the sample, the ultimate boundary the parameter can obtain, or the standard deviation of the sample values.

The weights, K, are used to reflect the influence of each parameter in determining the overall state-of-the-art. Two methods are proposed for determining the value of the weights. The first is a subjective technique and involves soliciting the opinions of experts on the system as to the relative importance of each parameter. The second method allows the analyst to make an explicit assumption about the growth pattern of the particular technology. To use this objective version of the technique, the analyst would first select an appropriate technology growth curve. The analyst would then equate the growth curve equation and the SOA equation

to determine the weights. The equation can be difficult to solve analytically and some form of numerical analysis is often required. This method will be discussed in more detail later in the chapter.

The remaining decision in applying the Gordon-Munson technique concerns the specification of the SOA equation. The equation presented at the beginning of this section is the arithmetic specification of the equation. An alternative is the multiplicative form.

$$SOA = P1/P1'[K2(P2/P2') + K3(P3/P3')+...+Kn(Pn/Pn')] \quad [2]$$

This form is appropriate for "cases in which one parameter must be present to some degree or the state of the art of the technology is zero" (9:4). An example of such a case is found in antibiotics. In this case, the critical parameter (P1) is the ability of the antibiotic to kill microorganisms. If the antibiotic cannot do this, the technology level is low, no matter what values have been achieved in other parameters.

The result of these decisions and manipulations is a technology index for the particular system. If reference values are selected such that $P < P'$ for all n parameters, and if the weights sum to unity, the index values will fall between zero and one. Therefore, "the index would represent the proximity of the current state of the art to the reference, and the index would have some physical significance to the analyst" (9:3).

System Identification

To facilitate the application of the Gordon-Munson technique in this research effort and to lend meaning to the results, the system to be studied should have the following characteristics:

1) A strong technological growth trend is evident over the life of the system.

2) A CER that does not include an explicit technology variable is available for the system.

3) An adequate technical and cost data base is available.

Military aircraft turbine engines possess each of these qualities and will be the system studied in this effort. Gordon and Edwards also used jet engines in an application of the Gordon-Munson technique; however, the particular engines used were different than the engines that will be used in this application (4:173). This prevents any comparison of the results from the studies.

Growth Trend. Aircraft turbine engines first made their appearance in the early 1940's and have since become the principal form of propulsion for the military, the commercial, and much of the general aviation fleets (13:43). The advancement of technology in jet engines

> ...is indicated by such improvements as replacing centrifugal compressors with axial flow compressors, the transition from uncooled to cooled turbines, the advance from single-design-point engines to multi-design-point engines, the replacement of aluminum and conventional steel by titanium and superalloys, the increase in aircraft speed from subsonic ranges through Mach 3, and the progression of engine type from turbojet to turboprop to turbofan (1:11).

This study will consider specifically turbojet and turbofan engines.

CER Baseline. In 1974, the Rand Corporation began developing CERs for aircraft turbine engines for the Air Force. The most recent update of these relationships was accomplished by Birkler in 1982 (2). Those revised CERs will serve as the baseline in this study to test the Gordon-Munson technology indices.

Birkler presented a CER for each of three types of aircraft turbine engine cost: development cost to MQT (MQTCOST), cumulative average unit production cost at 1000 units (PROCOST), and total development cost (TDEVCOST). Development cost to MQT includes all costs of the development of an engine up to the successful completion of its Model Qualification Test. The cumulative average unit production cost at 1000 units is self-explanatory. Total development cost includes the cost of development up to MQT plus "all subsequent product improvement during the life of the engine" (2:5).

Birkler limited the number of explanatory variables included in each CER. The reasons for this constraint were to improve the prediction variance and reduce the possibility of collinearity affecting the model. The result is that each CER contains only three independent variables. The MQTCOST CER contains thrust (THR), Mach number (MACH), and turbine inlet temperature (TIT). The PROCOST CER contains the same three independent variables

as the MQTCOST CER. The TDEVCOST CER contains THR, MACH, and quantity (QTY). THR is the maximum rated thrust at sea-level static conditions. MACH is the maximum flight envelope Mach number for an engine. TIT is the maximum turbine inlet temperature measured in degrees Rankine, and QTY is the quantity of engines produced.

Although acknowledging the fact that technology is a cost driver, Birkler did not include an explicit measure of technology in any of the CERs. Instead, he hypothesized that certain performance parameters would serve as a proxy for technology. TIT plays this role in the MQTCOST and PROCOST CERs, and no technology proxy is specifically identified in the TDEVCOST CER.

The CERs were duplicated for this study using a standard multiple linear regression package. The TDEVCOST and PROCOST CERs are identical to those presented in the Rand report. The MQTCOST CER has been reparameterized. This is because the J-58 engine, originally included in the Rand MQTCOST CER, was not used in this effort. The J-58 employs a type of propulsion technology (referred to as a ramjet) that is sufficiently different from the standard turbojet and turbofan propulsion to warrant its exclusion.

Rand used different engines in the data base of each CER. The data points used for the TDEVCOST CER include multiple points of the same engine. Each observation corresponds to a new version of the engine. These three baseline CERs are presented in Tables I-III.

TABLE I

Baseline MQTCOST CER

MQTCOST = A + B (TIT) + C (MACH) + D (THR)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	SIG T
A	-868.2261	144.0325	-6.0280	0.0001
B	0.2876	0.0721	3.9880	0.0021
C	290.3880	42.9232	6.7650	0.0000
D	0.0067	0.0027	2.5220	0.0284

R-SQUARE = .9335

MEAN SQUARE ERROR = 6201.590 F-RATIO = 51.4842

STANDARD ERROR OF THE ESTIMATE = 78.750 SIG F = 0.0000

TABLE II

Baseline PROCOST CER

PROCOST = A + B (THR) + C (TIT) + D (MACH)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	SIG T
A	-2228.1403	309.4478	-7.2000	0.0000
B	0.0430	0.0059	7.3190	0.0000
C	0.9688	0.1576	6.1480	0.0000
D	243.2499	81.1499	2.9980	0.0077

R-SQUARE = .9577

MEAN SQUARE ERROR = 33721.690 F-RATIO = 135.855

STANDARD ERROR OF THE ESTIMATE = 183.635 SIG F = 0.0000

TABLE III

Baseline TDEVCOST CER

TDEVCOST = A + B (MACH) + C (THR) + D (QTY)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	SIG T
A	-525.7630	132.4330	-3.9700	0.0005
B	401.0215	77.6411	5.1650	0.0000
C	0.0227	0.0056	4.0790	0.0004
D	0.0704	0.0203	3.4700	0.0019

R-SQUARE = .7881

MEAN SQUARE ERROR = 38438.269 F-RATIO = 30.9978

STANDARD ERROR OF THE ESTIMATE = 196.057 SIG F = 0.0000

Raw Data. This study requires both technical and cost data for aircraft turbine engines. The cost data was obtained from the Rand Corporation, is identical to that used by Birkler, and is proprietary in nature and cannot be presented. The Rand Corporation made three adjustments to the cost data for normalization: a price-level adjustment, a quantity adjustment, and a program adjustment. The technical data for all engines except the F-100, F-101, and F-404 was obtained from the Rand Corporation (2). The parameter values for these engines were obtained from the AFLC Engine Handbook (5) and ASD/YZ (3). The technical data is listed in Tables IV-VI.

Technology Index Methodology

This section outlines the steps necessary to construct the technology indices. The first subsection will cover the selected format of the Gordon-Munson SOA equation, while the second subsection will outline the solution algorithm to be employed.

Index Format. As stressed in the preceding section, the most critical decision in applying the Gordon-Munson quantification technique is the identification of the technology driven parameters used in the SOA equation. This study will draw from analysis done by Dr. J. P. Martino as presented in his report "An Investigation of the Tradeoff Surface Technique for Technology Measurement." Martino was also faced with the

TABLE IV

MQTCOST Data

ENGINE	TOA	THR	WGT	SFC	MACH	TIT
J57	41	10000	4160	0.80	1.4	2060
J65	46	7220	2815	0.92	1.2	2030
J71	47	9570	4090	0.88	1.5	2160
J79	57	15000	3225	0.87	2.0	2160
J75	59	23500	5950	0.80	2.0	2060
J60	71	3000	460	0.96	1.0	2060
TF33	71	17000	3900	0.52	1.0	2060
J52	74	8500	2050	0.82	1.8	2060
J85	74	3850	570	1.03	2.0	2100
TF30	92	18500	3850	0.63	2.2	2430
TF39	109	40800	7300	0.32	1.0	2840
TF34	120	9275	1420	0.36	1.0	2660
F100	126	23840	3021	0.72	2.5	3025
F101	135	30750	4382	0.58	2.2	3060
F404	148	16090	2161	0.81	2.0	2920

TABLE V

PROCOST Data

ENGINE	TOA	THR	WGT	SFC	MACH	TIT
J33	19	3825	1875	1.22	1.0	1960
J35	21	4000	2300	1.08	1.0	2010
J47	26	4850	2475	1.10	1.0	2060
J48	33	6250	2040	1.14	1.0	2030
J57	41	10000	4160	0.80	1.4	2060
J69	44	1025	364	1.12	1.0	1985
J65	46	7220	2815	0.92	1.2	2030
J71	47	9570	4090	0.88	1.5	2160
J73	49	8920	3825	0.92	1.9	2060
J79	57	15000	3225	0.87	2.0	2160
J75	59	23500	5950	0.80	2.0	2060
J60	71	3000	460	0.96	1.0	2060
TF33	71	17000	3900	0.52	1.0	2060
J52	74	8500	2050	0.82	1.8	2060
J85	74	3850	570	1.03	2.0	2100
TF30	92	20840	4112	0.63	2.5	2540
TF41	107	14500	3175	0.65	1.0	2620
TF39	109	40800	7300	0.32	1.0	2840
TF34	120	9275	1420	0.36	1.0	2660
F100	126	23840	3021	0.72	2.5	3025
F101	135	30750	4382	0.58	2.2	3060
F404	148	16090	2161	0.81	2.0	2920

TABLE VI

TDEVCOST Data

ENGINE	TOA	THR	WGT	SFC	MACH	TIT	QTY
J57	41	10000	4160	0.80	1.4	2060	1
J57	51	16000	5160	0.84	1.4	2060	1500
J79	57	15000	3225	0.87	2.0	2160	1
J75	59	23500	5950	0.80	2.0	2060	1
J57	59	16900	4750	0.83	1.4	2135	6500
J79	63	15800	3375	0.84	2.0	2160	400
J75	67	24500	5875	0.82	2.0	2070	400
TF33	71	17000	3900	0.52	1.0	2060	1
J60	71	3000	460	0.96	1.0	2060	1
J79	72	17000	3675	0.67	2.0	2235	1150
J52	74	8500	2050	0.82	1.8	2060	1
J85	74	3850	570	1.03	2.0	2100	1
TF33	82	21000	4605	0.61	1.0	2210	1200
J75	84	24500	5875	0.82	2.0	2070	1400
J85	85	4080	587	1.03	2.0	2160	1800
J52	91	9300	2118	0.86	1.8	2160	1700
TF30	92	18500	3852	0.63	2.2	2430	1
J60	96	3300	460	0.96	1.0	2060	800
J85	98	4300	600	1.04	2.0	2200	3700
J79	98	17900	3850	0.84	2.0	2270	7000
TF30	104	20840	4112	0.63	2.5	2540	1000
TF33	111	21000	4605	0.61	1.0	2210	2750
J52	111	11200	2318	0.89	1.8	2460	3500
F100	114	23840	3021	0.72	2.5	3025	1
TF30	115	25100	4027	0.69	2.5	2610	2500
TF34	120	9275	1420	0.36	1.0	2660	1
F100	136	23840	3021	0.72	2.5	3025	697
TF34	140	9275	1420	0.36	1.0	2660	651
F100	150	23840	3021	0.72	2.5	3025	1700

requirement for identifying critical technology parameters in his derivation of tradeoff surfaces. He presents a comprehensive analysis of jet engine design goals and identifies three critical technology driven parameters. This study will use those three parameters--maximum thrust, thrust-to-weight ratio and specific fuel consumption--as the variables in the SOA equation. Thrust (THR) is, once again, the maximum rated thrust at sea-level static condition, including afterburner thrust if any. This will be measured in pounds. Thrust-to-weight ratio (TTW) will simply be the maximum thrust of the engine divided by the engine's dry weight and will be a unitless number. Specific fuel consumption (SFC) will be measured at military thrust sea-level static conditions and will be in pounds of fuel per hour per pound-thrust units. SFC will be transformed to 1/SFC in keeping with the convention that variables be formatted such that larger values represent advances in technology. (SFC is a measure of fuel intake and a goal in system design is improved fuel efficiency). Martino adds that TIT, thrust-to-area ratio, and airflow might also be candidates for quantifying technological growth; however, for the purposes of this study only THR, TTW, and SFC will be analyzed. The values for the variables are either available in, or can be derived from, the data as described earlier. These variables will be normalized using the maximum observed sample value in each data set.

A constraint will be imposed on the equation that the weights associated with each variable will sum to unity. This condition combined with the choice of maximum sample value as the normalizing constant will result in indices that fall between zero and one.

Gordon and Munson present two types of functional relationships possible for the SOA model. The arithmetic specification will be employed here since low achievement of any single parameter does not degrade the technology level of the engine as a whole.

This effort will utilize the objective method of determining the value of the weights in the equation. This technique involves postulating a particular growth path of the technology over time. The technology forecasting community has spent considerable time and effort exploring trends in technology growth and have identified several types of growth patterns. Each pattern can be described by a certain function using time as the independent variable. The two types of growth patterns are the "S" shaped growth curve and the exponential growth curve.

One kind of "S" shaped growth curve is represented by the logistic function (Figure 2). This curve is appropriate for situations in which contributions from previous development efforts help to advance technology in new development efforts. In other words, a type of synergism is present as the system evolves over time (14). Both the hyperbolic tangent curve and the Pearl curve are

known as a logistic function. The other type of "S" shaped growth curve can be represented by the Gompertz curve (Figure 3). This curve is appropriate for types of systems in which development efforts are independent of each other and the achievements of one effort does not directly contribute to the ability to advance technology in a new development effort (14).

Functions represented by "S" shaped growth curves assume there is an upper bound on the ability to advance technology. Contrary to this, the exponential growth curve implies no upper bound, and is appropriate in systems for which there appears to be no limit to the technological growth possible (14). For this reason, the exponential curve is most often used to describe the combined growth of related technologies over time (Figure 4).

Gordon and Munson's objective technique involves equating the SOA equation with a particular growth curve and solving for the values of the weights in the SOA equation and the parameters (A and B) in the growth curve. This study will employ the objective technique using the hyperbolic tangent, Pearl, Gompertz and exponential curves. A linear trend will also be applied to the data for use as a base of comparison. The particular solution algorithm used to solve for the parameters and weights will be outlined in the next subsection. The results of this phase will be 15 SOA indices (five curves for three different

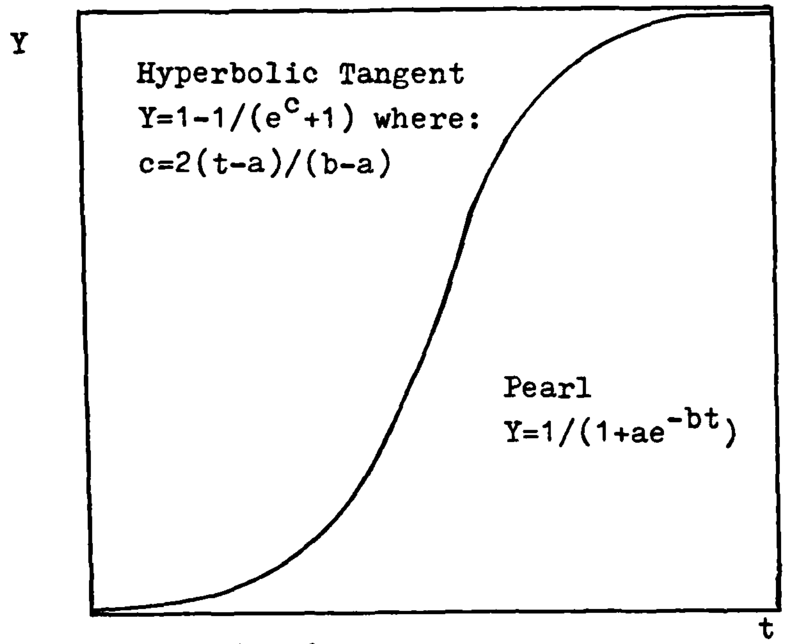

Fig. 2 Logistic Function

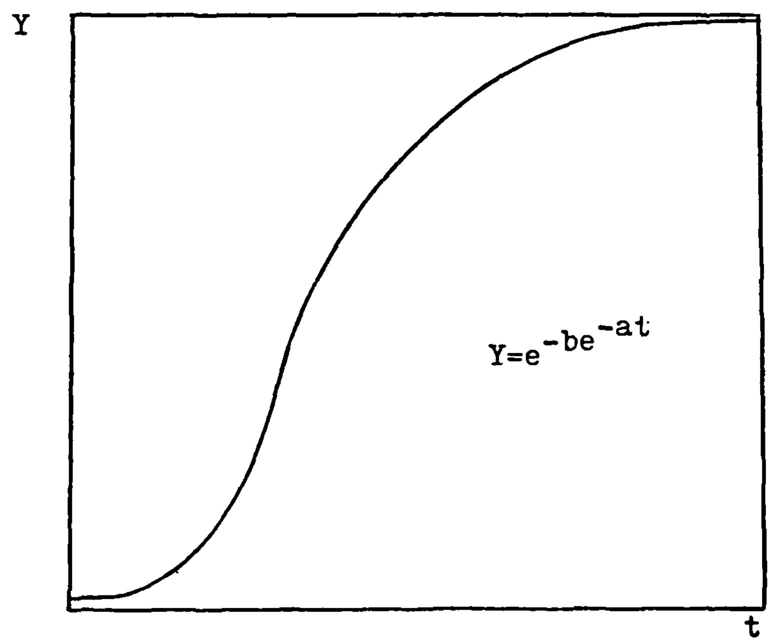

Fig. 3 Gompertz Function

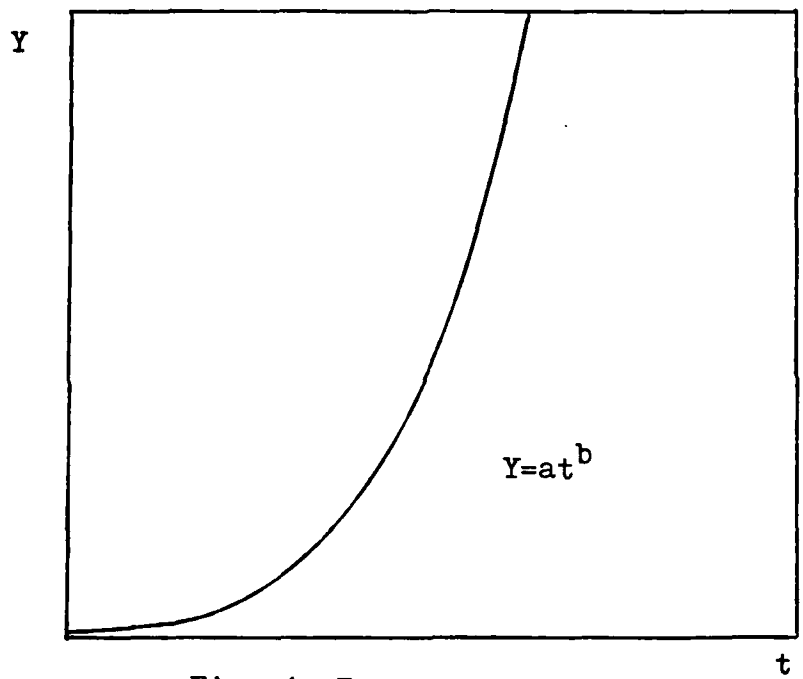

Fig. 4 Exponential Function

types of cost) to be used in exploring the nature of the relationship between technology and cost.

Solution Methodology. An example of an equation that must be solved is:

$$AT**B = K1(THR') + K2(TTW') + K3(SFC') \quad [3]$$

In this case, it is the exponential function. The prime notation is used to indicate normalized values for the variables. All the growth curves used in this application center around time as a variable and are described by two parameters, A and B. In general, A and B describe the shape of the curve. The specific meaning of A and B differ from one curve to another, but that has no direct bearing on this study. What does have an effect is the fact that the equation does not have a closed form solution and the values of the weights cannot be directly determined. Some type of iterative approach is necessary. This study will make use of the Gordon-Munson approach to the problem. Three steps are involved in each iteration of the solution approach. Each step makes use of a different computer program.

The computer programs for the first two steps of the solution technique were obtained from Dr. Gordon. Copies of these programs can be found in Appendix A. The multiple linear regression software package availiable on the Statistical Package for the Social Sciences (SPSS) will be used for the third step (19).

The first computer program accomplishes straightforward arithmetic calculations and requires the user to input the raw data and values for each weight (K). To begin the solution process, an initial value of 1/3 will be used for each K. The program first normalizes the data and then adjusts the input Ks to ensure they sum to unity. The program applies the Ks to the normalized data to produce an SOA index.

The second step fits a specified growth curve to the index generated in the first step. This program requires the user to input the SOA index along with the time (t) value for each SOA. For this study, TOA will be used for t. The program is based on a search algorithm that requires the user to input a starting range for the shape parameters (A and B). The program then attempts to solve for the values of the shape parameters that minimize the sum of the squared differences between the given SOAs and points on the curve. The program uses the final values of A and B to generate a list of calculated SOAs.

The third step is simply applying multiple linear regression to the calculated SOAs and the variables in the SOA equation. In this step, the calculated SOA serves as the dependent variable and is regressed against the SOA variables. The result is a set of least-squares-best-fit estimators of the weights associated with each variable. These coefficients are then entered in the first program (where they are adjusted so as to sum to unity) and the

second iteration begins. The process continues until successive iterations produce a change of less than 0.05% in the values of the weights. At this point, convergence is assumed.

Curve fitting is, at best, an uncertain science. There is no guarantee that the iterative process outlined above will result in convergence. In addition, there is no guarantee that the process will yield the truly optimal solution.

The final step in the index construction portion of this project will be an analysis of the final technology indices. Each index will be examined to determine the degree of fit between a curve and the index it produced. This will be accomplished by examining the results of the regression of the iteration producing convergence. The dependent variable values in the regression are the expected SOA values generated from the growth curve (step two). The fit will be analyzed by comparing these calculated values to the predicted values from the least-squares-best-fit equation. The differences are simply the residual values from the regression, and the size of the residuals will indicate the degree to which the final SOA equation is following the trend of the particular growth curve. The size of the residuals relative to the standard error will be examined to identify any outlying observations. Residuals larger than 2.0 standard devations will be subject to further examination. For these

situations, the size of the residual relative to the index value will be studied. Percent errors less than 25% of the index value will be considered acceptable.

CER Methodology

The final step of this study will be to incorporate the SOA indices in the appropriate CER. Each SOA will be added to the data base as an independent variable and then included in the estimating relationship with the original three cost drivers. The relationship will be presented and evaluated in terms of the impact of SOA on the value and significance of the coefficients, the size of the standard deviation of the coefficients, the improvement of the R-Square (coefficient of determination) of the model, the mean square error (MSE), the standard error of the estimate (SEE), and the overall F-ratio of the model.

IV. Data Analysis and Findings

The previous chapter outlined the methodology to be used in applying the Gordon-Munson technique to develop a technology variable for use in a CER. This chapter will offer the results of this application in two sections. The first section will present the SOA indices derived from the data while the second section will look at the relationship between the indices and the cost of turbine engines.

Technology Indices

Before applying the Gordon-Munson technique, the two computer programs provided by Dr. Gordon were validated. (The third program used is a standard multiple linear regression package). Dr. Gordon supplied data and results of an earlier application of the quantification technique to high temperature materials (4). The data was input to the recoded programs and the output matched the results of the earlier application. The curve used in this excercise was the hyperbolic tangent curve.

A total of fifteen SOA indices were generated in this application using the Gordon-Munson iterative solution approach; five curves applied to each of three data bases. For any one data base (MQTCOST, for example) the starting point for the solution algorithm was identical for all five growth curves. The solution algorithm was initiated for

all five curves by normalizing the data by the maximum sample value and multiplying each variable by an equal starting weight of 1/3. The result was an initial SOA index. The normalized data and initial index for MQTCOST data are presented in Table VII. Similarly, the starting points for TDEVCOST and PROCOST and listed in Tables VIII and IX respectively. The solution approach discussed in the methodology chapter was applied to the data and SOA indices were generated. The final weights and their level of significance along with the resulting SOA indices are presented in Tables X-XII. The progression of the weight values through the iterations of each application can be found in Appendix B. The input ranges for the parameter search in the curve fitting program are provided in Appendix C.

After developing the indices, each final index was analyzed for the degree of fit of the data to the hypothesized growth curve. This was accomplished by inspecting the regression results of the final iteration. Residuals for each index value were compared to the standard error of the estimate for the regression equation (Table XIII). The largest residual from the MQTCOST indices in each curve was for the F404 engine. None of these residuals exceeded 2.0 standard errors.

The PROCOST indices had one observation from each of the three "S" shaped curves with a residual larger than 2.0 standard errors. This residual was for the TF41

TABLE VII
MQTCOST Normalized Data
And Initial SOAs

ENGINE	TOA	THRUST	THR-TO-WGT	1/SFC	SOA
J57	41	.245	.305	.400	.317
J65	46	.177	.325	.348	.283
J71	47	.235	.297	.364	.299
J79	57	.368	.589	.368	.442
J75	59	.576	.500	.400	.492
J60	71	.074	.826	.333	.411
TF33	71	.417	.552	.615	.528
J52	74	.208	.525	.390	.374
J85	74	.094	.856	.311	.420
TF30	92	.453	.609	.508	.523
TF39	109	1.000	.708	1.000	.903
TF34	120	.227	.828	.889	.648
F100	126	.584	1.000	.444	.676
F101	135	.754	.889	.552	.732
F404	148	.394	.944	.395	.578

TABLE VIII
PROCOST Normalized Data
And Initial SOAs

ENGINE	TOA	THRUST	THR-TO-WGT	1/SFC	SOA
J33	19	.094	.259	.262	.205
J35	21	.098	.220	.296	.205
J47	26	.119	.248	.291	.219
J48	33	.153	.388	.281	.274
J57	41	.245	.305	.400	.317
J69	44	.025	.357	.286	.223
J65	46	.177	.325	.348	.283
J71	47	.235	.297	.364	.299
J73	49	.219	.296	.348	.288
J79	57	.368	.589	.368	.442
J75	59	.576	.500	.400	.492
J60	71	.074	.826	.333	.411
TF33	71	.417	.552	.615	.528
J52	74	.094	.856	.311	.420
J85	74	.208	.525	.390	.374
TF30	92	.511	.609	.508	.543
TF41	107	.355	.579	.492	.475
TF39	109	1.000	.708	1.000	.903
TF34	120	.227	.828	.889	.648
F100	126	.584	1.000	.444	.676
F101	135	.754	.889	.552	.732
F404	148	.394	.944	.395	.578

TABLE IX

TDEVCOST Normalized
Data And Initial SOAs

ENGINE	TOA	THRUST	THR-TO-WGT	1/SFC	SOA
J57	41	.398	.305	.450	.384
J57	51	.637	.393	.429	.486
J79	57	.598	.589	.414	.534
J75	59	.936	.500	.450	.629
J57	59	.673	.451	.434	.519
J79	63	.629	.593	.429	.550
J75	67	.976	.528	.439	.648
TF33	71	.677	.552	.692	.640
J60	71	.120	.826	.375	.440
J79	72	.677	.586	.537	.600
J52	74	.339	.525	.439	.434
J85	74	.153	.856	.350	.453
TF33	82	.837	.578	.590	.668
J75	84	.976	.528	.439	.648
J85	85	.163	.881	.350	.465
J52	91	.371	.556	.419	.449
TF30	92	.737	.609	.571	.639
J60	96	.131	.909	.375	.472
J85	98	.171	.908	.346	.475
J79	98	.713	.589	.429	.577
TF30	104	.830	.642	.571	.681
TF33	111	.837	.578	.590	.668
J52	111	.446	.612	.404	.487
F100	114	.950	1.000	.500	.817
TF30	115	1.000	.790	.522	.771
TF34	120	.370	.828	1.000	.733
F100	136	.950	1.000	.500	.817
TF34	140	.370	.828	1.000	.733
F100	150	.950	1.000	.500	.817

TABLE X

MQTCOST Final Weights and Indices

WEIGHTS

CURVE	K1	K2	K3
HYPERBOLIC TANGENT (HT)	.1489*	.6469**	.2043*
PEARL (PL)	.1484	.6453**	.2063*
GOMPERTZ (GOM)	.1382	.6489**	.2128*
EXPONENTIAL (EXP)	.1632	.6659**	.1710
LINEAR (LIN)	.1665	.6672**	.1663

* Significant at 80% confidence level
** Significant at 90% confidence level

STATE-OF-THE-ART (SOA) INDICES

TOA	ENGINE	HT	PL	GOM	EXP	LIN
41	J57	.315	.316	.317	.311	.311
46	J65	.308	.308	.309	.305	.304
47	J71	.301	.302	.303	.298	.298
57	J79	.511	.511	.511	.515	.515
59	J75	.491	.491	.489	.495	.496
71	J60	.613	.613	.617	.619	.619
71	TF33	.544	.545	.547	.541	.540
74	J52	.450	.450	.452	.450	.450
74	J85	.631	.630	.635	.638	.639
92	TF30	.565	.565	.566	.566	.566
109	TF39	.811	.812	.811	.806	.805
120	TF34	.751	.751	.758	.740	.738
126	F100	.825	.824	.824	.837	.838
135	F101	.800	.799	.799	.809	.810
148	F404	.750	.749	.751	.760	.761

TABLE XI

PROCOST Final Weights and Indices

WEIGHTS

CURVE	K1	K2	K3
HYPERBOLIC TANGENT (HT)	.1490*	.6310**	.2200*
PEARL (PL)	.1440*	.6342**	.2218*
GOMPERTZ (GOM)	.1421*	.6304**	.2275*
EXPONENTIAL (EXP)	.1580*	.6492**	.1928*
LINEAR (LIN)	.1536*	.6569**	.1896

* Significant at 80% confidence level
** Significant at 90% confidence level

STATE-OF-THE-ART (SOA) INDICES

TOA	ENGINE	HT	PL	GOM	EXP	LIN
19	J33	.235	.236	.236	.234	.234
21	J35	.219	.219	.220	.215	.216
26	J47	.238	.239	.239	.236	.236
33	J48	.329	.330	.330	.330	.332
41	J57	.317	.317	.318	.314	.314
44	J69	.292	.293	.294	.291	.293
46	J65	.308	.309	.309	.306	.307
47	J71	.302	.303	.303	.300	.300
49	J73	.296	.296	.297	.294	.294
57	J79	.507	.508	.507	.511	.513
59	J75	.489	.489	.488	.493	.493
71	J60	.606	.608	.607	.612	.617
71	TF33	.546	.547	.547	.543	.543
74	J52	.623	.625	.624	.631	.636
74	J85	.448	.449	.449	.449	.451
92	TF30	.572	.572	.572	.574	.575
107	TF41	.526	.527	.527	.527	.528
109	TF39	.816	.815	.816	.810	.808
120	TF34	.752	.755	.756	.745	.747
126	F100	.816	.817	.814	.827	.831
135	F101	.795	.795	.793	.803	.804
148	F404	.741	.743	.741	.751	.755

TABLE XII
TDEVCOST Final Weights and Indices

WEIGHTS*

CURVE	K1	K2	K3
HYPERBOLIC TANGENT (HT)	.1229	.5646	.3126
PEARL (PL)	.1225	.5655	.3120
GOMPERTZ (GOM)	.1223	.5722	.3055
EXPONENTIAL (EXP)	.1255	.5600	.3144
LINEAR (LIN)	.1266	.5580	.3154

* All weights significant at 90% confidence level

STATE-OF-THE-ART (SOA) INDICES

TOA	ENGINE	HT	PL	GOM	EXP	LIN
41	J57	.362	.362	.361	.362	.363
51	J57	.434	.434	.434	.435	.435
57	J79	.535	.536	.537	.535	.535
59	J75	.538	.538	.538	.539	.539
59	J57	.473	.473	.473	.474	.474
63	J79	.546	.546	.547	.546	.546
67	J75	.555	.555	.556	.556	.557
71	TF33	.611	.611	.610	.612	.621
71	J60	.598	.599	.602	.596	.594
72	J79	.582	.582	.582	.582	.582
74	J52	.475	.475	.476	.475	.474
74	J85	.611	.612	.615	.609	.607
82	TF33	.614	.613	.613	.614	.615
84	J75	.555	.555	.556	.556	.557
85	J85	.627	.627	.631	.624	.623
91	J52	.490	.491	.492	.490	.489
92	TF30	.613	.613	.613	.613	.613
96	J60	.646	.647	.651	.643	.642
98	J85	.642	.642	.646	.639	.637
98	J79	.554	.554	.555	.554	.554
104	TF30	.643	.643	.643	.643	.643
111	TF33	.614	.613	.613	.614	.615
111	J52	.527	.527	.528	.526	.525
114	F100	.838	.838	.841	.836	.836
115	TF30	.732	.732	.734	.732	.732
120	TF34	.825	.826	.825	.825	.824
136	F100	.838	.838	.841	.836	.836
140	TF34	.825	.826	.825	.825	.824
150	F100	.838	.838	.841	.836	.836

TABLE XIII

Summary of Largest SOA Residuals

MQTCOST

Curve	Stand Err	Resid	# Stand Err	% Err of Y
Hyp Tan	.07532	.1310	1.74	15.2
Pearl	.07727	.1329	1.72	15.3
Gompertz	.07206	.1190	1.65	14.0
Linear	.08216	.1597	1.94	17.9
Exp	.10141	.1946	1.92	20.5

PROCOST

Curve	Stand Err	Resid	# Stand Err	% Err of Y
Hyp Tan	.07527	.1611	2.14	23.5
Pearl	.07638	.1686	2.21	24.4
Gompertz	.07472	.1671	2.24	24.3
Linear	.07810	.1598	2.05	18.3
Exp	.09577	.1878	1.96	19.8

TDEVCOST

Curve	Stand Err	Resid	# Stand Err	% Err of Y
Hyp Tan	.05970	.1474	2.47	21.2
Pearl	.05914	.1462	2.47	20.9
Gompertz	.05980	.1463	2.45	20.9
Linear	.05941	.1454	2.45	20.9
Exp	.09432	.2313	2.45	31.7

engine. The associated percent error, however, was less than 25% of the index value. The largest residuals from the linear and exponential curves (less than 2.0 standard errors) were for the F404.

The TDEVCOST indices had one observation from every curve that exceeded 2.0 standard errors. In each case, the engine identified was the latest version of the J52. Examination of the associated percent errors revealed that only one surpassed 25%.

The results reflect a reasonably good fit of the data in each case. In general, the "S" shaped growth curves provided a much better fit of the data than did either the exponential or linear models. The exponential curve consistently provided the worst fit of the data. Though the F404 engine did not exceed the criterion for further analysis, it did appear often with a relatively large residual. This is because the values of THR and SFC for the F404 are somewhat inconsistent with engines falling in the same time period. The TF41 displayed the same characteristics as the F404. Examination of the J52 engine program, which appeared as the largest residual in the TDEVCOST indices, did not reveal any peculiarities that would explain its presence as a relative outlier.

Between data sets, the final weights of the technology variables were quite comparable. TTW was consistently identified as the parameter having the largest impact on the overall technology level of an engine. THR

and SFC were not as significant and suggests that these parameters may not have as much bearing on the technology level of jet engines. THR played the smallest role in determining SOA. This may be due to the recent inclination to build more efficient engines rather than advance the amount of thrust available in an engine. The tendency of the solution to give the majority of the weight to TTW and SFC confirms the trend towards efficiency as a design goal. SFC did not receive as much weight as was originally expected. One possible reason is that the three most recent engines have SFCs higher than the earlier data points. This reversal may have caused the solution procedure to assign less weight to SFC.

Within each data set, the results were surprising. Given the diversity of functional forms and theoretical implications among the growth curves, one would have expected differing results in the applications; however, the results do not bear this out. Overall, the sets of weights generated by each curve are remarkably alike. Closer inspection of the MQTCOST and PROCOST indices does reveal a slight pattern. The three "S" shaped curves produce nearly identical indices while the exponential and linear functions produce very similar indices. These groupings exist, but the distinction between groups is not as evident in the TDEVCOST indices.

The parallels between the indices within each data set were strong enough to remove the need to test each

index in each CER. Instead, a decision was made to test a representative of each grouping in the CERs. The hyperbolic tangent index was selected from the three "S" shaped curves and the linear index from the second grouping. These two indices were then applied in each of the three CERs.

Cost/Technology Relationship

The baseline CERs were presented in Chapter III. This section will be divided into three subsections; one for each baseline CER. To avoid confusion, it may be helpful to clarify some terms before presenting the analysis. The SOA indices referred to in each subsection are the indices generated from that particular database. For example, in the MQTCOST section, SOAH refers to the SOA index generated with the hyperbolic tangent curve from the variables in the MQTCOST database. In the PROCOST section, SOAH refers to the index generated using the hyperbolic tangent and the PROCOST database.

In each subsection, two new CERs were generated. One model included the original variables plus SOAH. A second model included the original variables plus SOAL (the SOA index resulting from the linear solution). At no time were both SOAH and SOAL included in the same CER.

MQTCOST. The first test was to check the correlation of the SOA indices with cost. The pairwise correlation matrix indicated a fairly strong relationship

between both indices and cost. All measures of correlation will be expressed by the R-Square value. The coefficient of determination (R-Square) between SOAH and cost was .43 The R-Square between SOAL and cost was also .43. This was equal to the correlation between THR and cost (.43) but below MACH (.58) and TIT (.62).

Stepwise multiple linear regression was applied to include the SOA indices in the baseline CER. For both indices, the stepwise procedure included the original three variables in the equation while SOA was left out. Given the relatively strong pairwise correlation between SOA and cost, collinearity was suspected as the cause for neither SOA being in the CER. Three checks were made for collinearity among independent variable.

As a lower bound test, pairwise correlations were examined. TIT and each SOA index registered a correlation (R-Square) of .69. This indicated a potential problem between the two variables. The next highest correlation between SOA and another independent variable was with THR measured at .30 for both indices.

As an upper bound check for collinearity, SOAL and SOAH were used as dependent variables and regressed against THR, MACH, and TIT. Using the stepwise procedure, only TIT entered the equation. Both indices registered an R-Square value of about .69 with TIT. When the other two variables were forced in with TIT, the R-Square only improved to .71.

As a final check, SOAH and SOAL were forced into the cost equations as independent variables along with THR, MACH, and TIT. The statistics are shown in Tables XIV and XV. The purpose of this step was to check if the addition of SOA caused fluctuations in the parameter estimates and/or an inflation in the standard errors of the parameters as compared to the baseline CER. For both indices, all values were relatively stable except the standard error of the parameter estimate on TIT. This jumped from .072 to .113, an increase of more than 50%.

The checks all indicated a collinear relationship between each index and TIT. As a result, TIT was excluded from the equation and a CER was created using only SOA, THR, and MACH as independent variables. This was accomplished for both SOAL and SOAH. The CERs are listed in Tables XVI and XVII. In each case, SOA entered the equation on the third step and the parameter estimates were statistically significant. The SOA CERs were not quite as impressive as the baseline CER. The baseline CER provided a slightly higher R-Square, a more significant F-Ratio and a smaller standard error of the estimate. Nonetheless, the SOA CERs are respectable estimating relationships.

PROCOST. The effects of adding the SOA indices to the PROCOST CER were much the same as in MQTCOST. The pairwise correlation matrix again showed a fairly strong relationship between each SOA index and cost. SOAH registered an R-Square of .60 with cost, while SOAL

TABLE XIV

SOAH Added to the Baseline MQTCOST CER

MQTCOST = A + B (TIT) + C (MACH) + D (THR) + E (SOAH)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	SIG T
A	-840.9652	164.3702	-5.1160	0.0005
B	0.2534	0.1132	2.2380	0.0492
C	292.7116	45.0258	6.5010	0.0001
D	.0067	0.0028	2.4240	0.0358
E	87.0796	164.3702	0.4040	0.6950

R-SQUARE = .9346

MEAN SQUARE ERROR = 6712.4337   F-RATIO = 35.7152

STANDARD ERROR OF THE ESTIMATE = 81.9294   SIG F = 0.0000

TABLE XV

SOAL Added to the Baseline MQTCOST CER

MQTCOST = A + B (TIT) + C (MACH) + D (THR) + E (SOAL)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	SIG T
A	-836.1284	165.2170	-5.0610	0.0005
B	0.2495	0.1121	2.2260	0.0502
C	291.9492	44.6837	6.5330	0.0001
D	0.0067	0.0028	2.4320	0.0353
E	96.3591	211.0574	0.4570	0.6577

R-SQUARE = .9349

MEAN SQUARE ERROR = 6682.4589   F-RATIO = 35.8867

STANDARD ERROR OF THE ESTIMATE = 81.7463   SIG F = 0.0000

TABLE XVI

MQTCOST SOAH CER

MQTCOST = A + B (MACH) + C (THR) + D (SOAH)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	SIG T
A	-535.3941	106.8760	-5.0090	0.0004
B	321.1055	50.4611	6.3630	0.0001
C	0.0093	0.0029	3.1800	0.0088
D	448.7044	167.0299	2.6860	0.0212

R-SQUARE = .9018

MEAN SQUARE ERROR = 9158.111 F-RATIO = 33.6798

STANDARD ERROR OF THE ESTIMATE = 95.698 SIG = 0.0000

TABLE XVII

MQTCOST SOAL CER

MQTCOST = A + B (MACH) + C (THR) + D (SOAL)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	SIG T
A	-527.2786	104.5584	-5.0430	0.0001
B	316.3607	50.5098	6.2630	0.0001
C	0.0094	0.0029	3.2180	0.0082
D	445.9966	164.3494	2.7140	0.0202

R-SQUARE = .9026

MEAN SQUARE ERROR = 9084.487 F-RATIO = 33.9825

STANDARD ERROR OF THE ESTIMATE = 95.313 SIG F = 0.0000

measured .59. This was higher than MACH (.31) but below THR (.82) and TIT (.79).

An attempt to include the indices in the baseline CER was made using the stepwise regression procedure. Neither SOA index was accepted in the CER.

The same three checks for collinearity applied in MQTCOST were accomplished here. The pairwise correlation among the independent variables showed a fairly significant correlation between the SOA indices and TIT. Both SOAH and SOAL had an R-Square of .70 with TIT. The next highest correlation was with THR. Both indices registered an R-Square of about .47 with THR.

Both SOAH and SOAL were used as the dependent variables and regressed against THR, MACH and TIT. The results of the two regressions were virtually identical. Using the stepwise procedure, TIT was the only variable to enter the equation with an R-Square of .70. With all three variables forced into the equation, the R-Square only increased to .72.

The final check for collinearity consisted of forcing the inclusion of SOA with the original independent variables in the baseline CER. The statistics are shown in Tables XVIII and XIX. The effects of SOAH and SOAL were very similar. When either index was included, the parameters and standard errors associated with THR and MACH remained relatively stable. The parameter value for TIT

TABLE XVIII

SOAH Added to the Baseline PROCOST CER

PROCOST = A + B (THR) + C (TIT) + D (MACH) + E (SOAH)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	SIG T
A	-2382.9378	351.8458	-6.7730	0.0000
B	0.0442	0.0060	7.3310	0.0000
C	1.0983	0.2101	5.2280	0.0001
D	250.7069	81.8211	3.0640	0.0070
E	-343.7845	367.4206	-0.9360	0.3625

R-SQUARE = .9598

MEAN SQUARE ERROR = 33956.597 F-RATIO = 101.404

STANDARD ERROR OF THE ESTIMATE = 184.273 SIG F = 0.0000

TABLE XIX

SOAL Added to the Baseline PROCOST CER

PROCOST = A + B (THR) + C (TIT) + D (MACH) + E (SOAL)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	SIG T
A	-2387.7952	354.8306	-6.7420	0.0000
B	0.0440	0.0060	7.3440	0.0000
C	1.0989	0.2102	5.2280	0.0001
D	253.1220	82.1035	3.0830	0.0067
E	-337.2644	359.8306	-0.9370	0.3617

R-SQUARE = .9598

MEAN SQUARE ERROR = 33950.847 F-RATIO = 101.423

STANDARD ERROR OF THE ESTIMATE = 184.258 SIG F = 0.0000

increased slightly and the standard error increased from .15 to .21, or roughly 40%. It is interesting to note the the parameter value assigned to the index in both cases carried a negative sign.

Once again, it appeared that the SOA indices were correlated to TIT. As a result, the model was run excluding TIT from the equation. The results are presented in Tables XX and XXI. Once again, neither SOA CER had quite as significant statisitics as the baseline CER. The SOA indices, however, can serve as viable substitutes for TIT in the CERs.

TDEVCOST. At first glance, the results of the application of SOAH and SOAL to the TDEVOCST CER did not appear to follow the pattern set by MQTCOST and PROCOST. Further examination, however, revealed that this application paralleled the previous two.

The pairwise correlation matrix showed the SOA indices to be less correlated with cost than in either MQTCOST or PROCOST. The R-Square value between SOAH and cost was .14. This was identical to the correlation between QTY and cost, but less than either THR (.44) or MACH (.53) and cost. SOAL also had an R-Square value of .14 with cost.

When the indices were added to the baseline CER, the stepwise procedure added each SOA index as the fourth variable. The statistics for each index are displayed in Tables XXII and XXIII and are virtually identical. Both

TABLE XX

PROCOST SOAH CER

PROCOST = A + B (THR) + C (MACH) + D (SOAH)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	SIG T
A	-681.5581	209.8066	-3.2490	0.0045
B	0.0555	0.0088	6.2990	0.0000
C	287.6030	127.9234	2.2480	0.0373
D	920.7831	433.9996	2.1220	0.0480

R-SQUARE = .8951

MEAN SQUARE ERROR = 83625.134 F-RATIO = 51.2026

STANDARD ERROR OF THE ESTIMATE = 289.180 SIG F = 0.0000

TABLE XXI

PROCOST SOAL CER

PROCOST = A + B (THR) + C (MACH) + D (SOAL)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	SIG T
A	-669.7850	207.1394	-3.2330	0.0046
B	0.0559	0.0087	6.4280	0.0000
C	281.1499	128.5706	2.1870	0.0422
D	901.7938	424.8763	2.1220	0.0479

R-SQUARE = .8951

MEAN SQUARE ERROR = 83611.515 F-RATIO = 51.2119

STANDARD ERROR OF THE ESTIMATE = 289.157 SIG F = 0.0000

TABLE XXII

SOAH Added to Baseline TDEVCOST CER

TDEVCOST = A + B (MACH) + C (THR) + D (QTY) + E (SOAH)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	SIG T
A	-973.6749	180.2569	-5.4020	0.0000
B	372.3928	66.9855	5.5590	0.0000
C	0.0208	0.0048	4.3220	0.0002
D	0.0807	0.0177	4.5720	0.0001
E	840.6721	263.2408	3.1940	0.0039

R-SQUARE = .8513

MEAN SQUARE ERROR = 28099.176 F-RATIO = 34.3523

STANDARD ERROR OF THE ESTIMATE = 167.628 SIG F = 0.0000

TABLE XXIII

SOAL Added to the Baseline TDEVCOST CER

TDEVCOST = A + B (MACH) + C (THR) + D (QTY) + E (SOAL)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	SIG T
A	-976.4756	180.8184	-5.4000	0.0000
B	373.5694	66.9180	5.5820	0.0000
C	0.0206	0.0048	4.2710	0.0003
D	0.0808	0.0177	4.5780	0.0001
E	847.8775	265.2508	3.1970	0.0039

R-SQUARE = .8514

MEAN SQUARE ERROR = 28083.621 F-RATIO = 34.3746

STANDARD ERROR OF THE ESTIMATE = 167.582 SIG F = 0.0000

CERs offer improved statistical properties over the baseline. SOA was able to account for a portion of the unexplained error in the baseline CER without adding any significant collinearity problems.

In his reporting of the original CERs, Birkler mentioned that TIT could be included in the TDEVCOST CER. He chose to exclude it to keep the number of independent variables in the model to a minimum. Before the SOA indices could be judged as improving the estimating accuracy of the model, they had to be compared with the contribution TIT made to explaining cost.

A model was constructed using an SOA index, THR, MACH, QTY, and TIT as independent variables. Stepwise regression was applied and the results are presented in Table XXIV. No matter which SOA index was used, the procedure selected TIT to enter the equation on the fourth step and excluded SOA. The statistics of the CER with TIT in the equation (Table XXIV) were slightly better than with either SOA index in the equation (Tables XXII and XXIII). The upper and lower bound collinearity checks were accomplished and the results were the same as in MQTCOST and PROCOST. Both SOA indices were correlated with TIT.

TABLE XXIV

TIT Added to the Baseline TDEVCOST CER

TDEVCOST = A + B (MACH) + C (THR) + D (QTY) + E (TIT)

COEFF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	SIG T
A	-1259.6497	232.2629	-5.4230	0.0000
B	319.6583	67.9004	4.7080	0.0001
C	0.0188	0.0047	3.9900	0.0005
D	0.0743	0.0168	4.4340	0.0002
E	0.4034	0.1127	3.5790	0.0015

R-SQUARE = .8619

MEAN SQUARE ERROR = 26103.912 F-RATIO = 37.4366

STANDARD ERROR OF THE ESTIMATE = 161.567 SIG F = 0.0000

Summary

The CER statistics are briefly summarized in Tables XV - XVII. In each data base, the SOA indices were statistically correlated to TIT. SOA proved to be a valid cost driver for aircraft turbine engines, but the collinearity between the SOA and TIT prevented SOA from joining the original independent variables in the equation to improve the estimating accuracy of the baseline CERs.

TABLE XXV

MQTCOST Summary

VARIABLES	GROWTH CURVE	R-SQUARE	F-RATIO	STANDARD ERROR OF THE ESTIMATE
THR MACH TIT	NONE*	.9335	51.48	78.75
THR MACH SOA	HT	.9018	33.68	95.70
THR MACH SOA	LIN	.9038	34.43	94.75

(* indicates baseline CER)

TABLE XXVI

PROCOST Summary

VARIABLES	GROWTH CURVE	R-SQUARE	F-RATIO	STANDARD ERROR OF THE ESTIMATE
THR MACH TIT	NONE*	.9577	135.85	183.63
THR MACH SOA	HT	.8951	51.20	289.18
THR MACH SOA	LIN	.8951	51.21	189.16

(* indicates baseline CER)

TABLE XXVII

TDEVCOST Summary

VARIABLES	GROWTH CURVE	R-SQUARE	F-RATIO	STANDARD ERROR OF THE ESTIMATE
THR MACH QTY	NONE*	.7881	30.99	196.06
THR MACH QTY SOA	HT	.8513	34.35	167.63
THR MACH QTY SOA	LIN	.8514	34.37	167.58
THR MACH QTY TIT	NONE	.8619	37.44	161.57

(* indicates baseline CER)

V. Conclusions and Recommendations

Conclusions

Accounting for the cost impact of advances in the technological state-of-the-art of a system has been, and will continue to be a serious concern of the cost estimating community. The need to quantify the cost of technological advance is especially acute in the early stages of system design where parametric estimating relationships are the primary method of generating the cost estimate. This research effort has demonstrated that the Gordon-Munson technique for quantifying the technological level of a system is a viable method to address that need. The application of the technique to aircraft turbine engines produced an SOA index that proved to be a valid cost driver in a CER.

The turbine engine SOA indices derived in this study were consistently correlated to the TIT parameter. This result has several implications. The substitution of SOA for TIT resulted in CERs that were not quite as statistically significant as the baseline CERs. This statistical degradation is slight and is more than outweighed by the benefits of explicitly accounting for technological advance. In presenting the baseline CERs, Birkler suggested that the contribution of TIT to the CERs lay in the ability of the parameter to measure the

performance and technology level of the system. The correlation of TIT and SOA does indeed indicate that TIT has been a reasonable surrogate for a technological variable. A potential danger exists, however, in relying on a single parameter to account for the technology level of a system. Given the resource constraints that now surround new system development, tradeoffs between performance parameters are inevitable. Should a new system be designed that incorporates new technology in areas other than that described by the technology proxy, the estimate for the new system will not include that cost of the technological advance. An explicit technology measure like the SOA index reduces this type of risk. SOA attempts to include all key parameters that are linked to advances in the technological level of a system. Tradeoffs are accounted for in the measure and the inclusion of SOA in a CER reduces the chance of underestimating due to neglecting the cost of technological advance.

Strengths and Weaknesses

The major strength of this research effort originates from the fact that the Gordon-Munson technique is an accepted model of technological advance. The technique was presented and then further tested in a series of two articles appearing in the professional journal of the technological forecastinn field. The model offers a rational and logical methodology for measuring

technological advance and has received favorable comment from experts in the field (14). Gordon and Munson present the technique in sufficient detail to allow a credible application in this study. In addition, Dr. Gordon provided invaluable assistance in the particulars of applying the objective version of the technique. The results of this study derive their strength from the rigorous application of a proven concept.

This report benefitted from the existence of established CERs for aircraft turbine engines. The CERs are current, well-supported and well-documented. The Rand CERs provided a firm baseline from which to evaluate the effect of the technology indices.

Another strength lies in the use of the objective version of the Gordon-Munson technique. By objectively solving for the weights of the parameters, the solution is free from the influence of subjective evaluations. In addition, the application of an objective method will allow a more critical analysis and evaluation of the indices presented in this document.

Unfortunately, the objective solution methodology is also a source of weakness in this study. The problem resides in the solution of shape parameters for each growth curve. The curve fitting program employed in this study used a search algorithm to locate the best possible value for the parameters. The problem with this type of numerical analysis is that the resulting solution cannot be

labeled as the global optimum solution. The final weights could therefore be only one of a possible set of solutions to the equations with no way to prove optimality.

The selection of THR, TTW, and SFC as the key technology parameters is another possible weakness of this application. The Gordon-Munson technique calls for the inclusion of those parameters that are critical to defining technological advance in a particular system. THR is a questionable selection from an intuitive point of view. It is not certain that an increase in the technology level of an engine would necessarily be accompanied by an increase in the thrust available from an engine. The mission of the new engine (for example: fighter vs. cargo) tends to drive the thrust requirement of engine developments. SFC is questionable from more of a practical point of view. Regardless of the mission of the engine, one would expect a major design goal to be improved fuel efficiency. The three most current data points in each data set, however, contain SFC values larger than those achieved in earlier engine developments. As mentioned previously, this phenomenon was the most likely cause of SFC receiving a fairly small weighting in the final indices.

Finally, the success possibilities of this research effort were somewhat limited by the choice of the baseline CERs. The Rand CERs were excellent estimating relationships with impressive statistical properties. The goal was to apply the Gordon-Munson technique to improve

estimating accuracy. The baseline MQTCOST and PROCOST CERs, however, already explained a very large portion of the variation in cost. This left only a small part of the variation in cost availiable for SOA to help explain. This is part of the reason why SOA had trouble entering the relationships. In fact, this situation may have kept SOA out of the CERs even if the index had not been correlated with TIT. The TDEVCOST CER showed more promise as a candidate to test the SOA indices, but the addition of TIT to the baseline CER improved the statistics and diminished the chances of SOA contributing to the model.

Recommendations for Future Research

The application of the Gordon-Munson technique for deriving a technology index for a CER is a significant step forward in addressing the problem of accounting for the cost of technological advance in new systems. This application to jet engines needs to be expanded and there are several possible areas for future research. In addition, the technique holds great potential for other systems that are highly sensitive to technological advance (avionics is an example). Specific recommendations for future research are:

- Reapply the Gordon-Munson technique to jet engines with a new set of technology parameters. The correlation between the SOA developed in this study and TIT indicates that TIT is a prime candidate for a technology variable. Also, Dr. Martino suggested other technology driven parameters. These would also be candidates for the SOA indices.

- The specification to the variables in the SOA equations can be modified. A variable may be respecified (for example, the squared value of the parameter) to improve the fit of the data to the growth curves.

- The SOA indices could be respecified to explore the relationship of cost and technological advance. For example, the CER may be improved if the square root of SOA were included in the relationship. This would imply a different relationship between cost and technology than was explored in this study.

- Apply the subjective version of the Gordon-Munson technique to jet engines. Comparison between the objective and subjective weights and the contribution of the resulting indices to jet engine CERs would be of value in evaluating the two versions of the Gordon-Munson technique.

- The Gordon-Munson technique needs to be applied and tested in CERs for other systems. Obvious candidates are avionics and unmanned spacecraft. These weapon systems are subject to a high degree of technological advance.

Appendix A: Computer Programs

Program 1: Data Normalization

```
100 PRINT
120 A$="STATE OF THE ART CALCULATIONS"
130 B$="JET ENGINES"
140 D$="JULY 12, 1984"
150 Q$="................................................."
160 READ P,N
170 DIM C$(30): DIM W(30)
180 DIM C(30,5): DIM D(30,5)
190 DIM Z(30,5): DIM X(30,5)
195 DIM L(30,5)
210 FOR J=1 TO P+2
220 READ N$(J)
230 NEXT J
240 FOR I=1 TO N
250 READ C$(I)
260 FOR J=1 TO P+1
270 READ C(I,J)
280 NEXT J
290 NEXT I
300 REM SET INITIAL VALUES FOR A
310 FOR J=2 TO P+1
320 A(J)=C(1,J)
330 NEXT J
340 FOR J=2 TO P+2
350 READ K(J)
360 NEXT J
370 FOR J=2 TO P+2
380 K9=K9+K(J)
390 NEXT J
400 FOR J=1 TO P+2
410 K(J)=K(J)/K9
420 NEXT J
430 REM FIND THE HIGHEST IN EACH COLUMN
440 FOR J=2 TO P+1
450 FOR I=1 TO N
460 IF C(I,J)>A(J) THEN A(J)=C(I,J)
480 NEXT I: NEXT J
490 REM COMPUTE THE NORMALIZED VALUE OF EACH PARAMETER
500 FOR J=1 TO P+1
510 FOR I=1 TO N
520 IF J<>1 THEN GOTO 540
530 D(I,1)=C(I,1)
540 IF J=1 THEN GOTO 570
550 D(I,J)=C(I,J)/A(J)
560 D(I,J)=INT(D(I,J)*1000+.5)/1000
570 NEXT I: NEXT J
580 REM COMPUTE THE SOA
```

```
581 FOR I=1 TO N
582 D(I,P+2)-1
583 NEXT I
590 FOR I=1 TO N
600 FOR J=2 TO P+2
610 L(I,J)=K(J+1)*D(I,J)
620 NEXT J: NEXT I
630 FOR I=1 TO N
640 FOR J=2 TO P+2
650 W(I)=W(I)+L(I,J)
660 NEXT J: NEXT I
670 FOR I=1 TO N
680 W(I)=INT(W(I)*1000+.5)/1000
690 NEXT I
700 PRINT Q$
710 PRINT
720 Z$=A$
730 GOSUB 1030
740 Z$=B$
750 GOSUB 1030
760 PRINT
770 PRINT D$
771 PRINT
772 PRINT Q$
773 PRINT: PRINT
780 PRINT "GIVEN DATA"
790 PRINT Q$
820 FOR I=1 TO N
830 FOR J=1 TO P+1
840 Z(I,J)=C(I,J)
850 NEXT J: NEXT I
860 GOSUB 1070
870 K1=1
880 PRINT: PRINT: PRINT
890 PRINT "NORMALIZED DATA"
900 PRINT Q$
930 FOR I=1 TO N
940 FOR J=1 TO P+1
950 Z(I,J)=D(I,J)
960 NEXT J: NEXT I
970 GOSUB 1070
980 PRINT
982 IF K(2)=0 THEN GOTO 990
985 PRINT "CONSTANT=", K(2)
990 FOR J=3 TO P+2
995 PRINT
1000 PRINT "K(";(J-2);")=   ";K(J)
1010 NEXT J
1015 PRINT Q$
1020 END
1030 REM PRINT SUBROUTINE
```

```
1040 PRINT Z$
1060 RETURN
1070 REM PRINT NORMALIZED DATA
1080 IF K1=0 THEN GOTO 1200
1090 S$= "!     ###     #.###       #.###        #.###    #.###"
1100 PRINT "     YEAR     THRUST     THR-TO-WGT    1/SFC      SOA"
1110 FOR I=1 TO N
1120 PRINT USING S$ C$(I),Z(I,1),Z(I,2),Z(I,3),Z(I,4),W(I)
1130 NEXT I
1135 PRINT Q$
1140 RETURN
1200 REM PRINT RAW DATA
1210 T$= "!     ###      #####      #.####       #.####"
1220 PRINT "     YEAR     THRUST     THR-TO-WGT     1/SFC"
1230 FOR I=1 TO N
1231 PRINT USING T$ C$(I),Z(I,1),Z(I,2),Z(I,3),Z(I,4)
1232 NEXT I
1240 PRINT Q$
1250 RETURN
1260 REM NUMBER OF PARAMETERS, NUMBER OF DATA POINTS
1270 DATA 3,15
1280 REM NAMES OF PARAMETERS
1290 DATA YEAR,THRUST,THR-TO-WGT,1/SFC,SOA
1300 REM YEAR, VALUES OF PARAMETERS
1300 DATA A,41,10000,2.4038,1.2500
1320 DATA B,46,7220,2.5648,1.0870
1330 DATA C,47,9570,2.3399,1.1364
1340 DATA D,57,15000,4.6512,1.1494
1350 DATA E,59,23500,3.9496,1.2500
1360 DATA F,71,3000,6.5217,1.0417
1370 DATA G,71,17000,4.3590,1.9231
1380 DATA H,74,8500,4.1463,1.2195
1390 DATA I,74,3850,6.7544,.9709
1400 DATA J,92,18500,4.8052,1.5873
1410 DATA K,109,40800,5.589,3.1250
1420 DATA L,120,9275,6.5317,2.7778
1430 DATA M,126,23840,7.8914,1.3889
1440 DATA N,135,30750,7.0173,1.7241
1450 DATA O,148,16090,7.4456,1.2346
1460 REM CONSTANT, COEFFICIENTS
1470 DATA 0,.12981..56445,.18050
EOT..
```

Program 2: Curve Fitting

```
100 W=1
110 REM NO OF ITERATION
120 WC=10
130 Z=5000
150 PRINT
160 DIM X(50):DIM Y(50):DIM H(1000)
165 DIM YC(50)
170 PRINT"THIS IS A LEAST SQUARES FITTING PROGRAM"
180 PRINT
190 PRINT"FUNCTION FITTED IS SHOWN ON LINES 570,800,AND 1100"
200 PRINT
230 FOR I=1 TO 50
250 READ X(I)
260 IF X(I)=999 THEN GOTO 300
270 READ Y(I)
290 NEXT I
300 N=I-1
310 PRINT
320 PRINT "HERE IS THE DATA TABLE"
330 PRINT  "POINT              YEAR               SOA"
340 FOR I=1 TO N
350 PRINT I,X(I),Y(I)
360 NEXT I
370 PRINT:PRINT"ANY CHANGES (Y/N)"
380 INPUT A$: IF A$="N" GOTO 450
390 PRINT "WHAT POINT";:INPUT I
400 PRINT "X(I)=";:INPUT X(I)
410 PRINT "Y(I)=";:INPUT Y(I)
420 PRINT:PRINT"MORE (Y/N)"
430 INPUT A$: IF A$="Y" GOTO 390
440 PRINT: GOTO 320
450 PRINT
451 C1=X(N/2): C2=X(N)
452 PRINT "SUGGESTION:"
453 PRINT "FIRST  CONSTANT MIGHT BE:";C1
454 PRINT "SECOND CONSTANT MIGHT BE:";C2
455 PRINT
459 PRINT" NOW PROVIDE AN ESTIMATE FOR THE LIMITS TO THE FIRST CONSTANT:"
460 PRINT"     LOWER LIMIT";:INPUT A1(1)
470 PRINT"     UPPER LIMIT";:INPUT A1(2)
475 R1=A1(2)-A1(1)
480 PRINT
490 PRINT"NOW THE SECOND CONSTANT"
500 PRINT"     LOWER LIMIT";:INPUT A2(1)
510 PRINT"     UPPER LIMIT";:INPUT A2(2)
```

```
515 R2=A2(2)-A2(1)
520 PRINT
530 REM: FIRST A RANDOMIZED SEARCH
535 PRINT
537 RANDOM(0)
540 FOR J=1 TO 100
547 B1=(RND*R1)+A1(1)
548 B2=(RND*R2)+A2(1)
560 FOR I=1 TO N
570 YC(I)= 1/(1+(B1*EXP(-B2*X(I))))
580 E=(YC(I)-Y(I))**2
590 F=F+E
600 G=F**.5
610 H(J)=G
620 NEXT I
625 S=INT(Z*100+.5)/100
640 G=0: E=0: F=0
650 IF H(J) < Z THEN R=B1
660 IF H(J) < Z THEN T=B2
670 IF H(J) < Z THEN Z=H(J)
675 C3(W)=Z
680 J=J+1
690 NEXT J
692 PRINT
705 IF C3(W-1)=C3(W) THEN GOTO 970
710 PRINT"THE COEFFICIENTS FOR THE BEST FIT ARE:"
720 PRINT
730 PRINT "B1=";R,"LOWER LMT=";A1(1),"UPPER LMT=";A1(2)
740 PRINT "B2=";T,"LOWER LMT=";A2(1),"UPPER LMT=";A2(2)
750 PRINT "ITERATION=";W
760 PRINT "SR SUM OF SQ=";Z
770 PRINT " YEAR              GIVEN                FIT"
780 YA=0: YB=0: YC=0: YE=0: YF=0
790 FOR I=1 TO N
800 YC(I)=1/(1+(R*EXP(-T*X(I))))
810 YA=YA+Y(I)
820 NEXT I
830 YB=YA/N
840 FOR I=1 TO N
850 YC=(Y(I)-YC(I))**2
860 YD=YD+YC
870 YE=(Y(I)-YB)**2
880 YF=YF+YE
890 NEXT I
900 FOR I=1 TO N
910 PRINT X(I),Y(I),YC(I)
920 NEXT I
930 PR=(1-(YD/YF))
940 PRINT
950 PRINT "R SQUARED=";PR
960 PRINT:PRINT
```

```
961 FOR I=1 TO N
963 NEXT I
970 A1(2)=R+(.5/W)*R1
980 A1(1)=R-(.5/W)*R1
990 A2(2)=T+(.5/W)*R2
1000 A2(1)=T-(.5/W)*R2
1010 G=0: E=0: F=0: W=W+1
1020 IF W>WC THEN GOTO 1040
1030 GOTO 540
1040 PRINT
1050 PRINT"TRY OTHER POINTS (Y/N)"
1060 INPUT A$
1070 IF A$="N" GOTO 1140
1080 PRINT"WHAT YEAR?"
1090 INPUT X(I)
1105 YC(I)= 1/(1+(R*EXP(-T*X(I))))
1110 PRINT "VALUE=";YC(I)
1120 PRINT X(I),"    ", YC(I)
1130 GOTO 1050
1140 END
1150 DATA 41,.316,46,.308,47,.302,57,.511,59,.491,71,.613,71,.545
1160 DATA 74,.450,74,.630,92,.565,109,.812,120,.751,126,.824,135,.799
1170 DATA 148,.749
1175 DATA 999
EOT..
```

Appendix B: Iteration Weights

MQTCOST Iteration Weights

CURVE	ITERATION	K1	K2	K3
HYPERBOLIC TANGENT	Initial	.3333	.3333	.3333
	Iteration 1	.1614	.6540	.1847
	Iteration 2	.1492	.6444	.2063
	Iteration 3	.1489	.6469	.2143
PEARL	Initial	.3333	.3333	.3333
	Iteration 1	.1603	.6539	.1864
	Iteration 2	.1484	.6453	.2063
	Iteration 3	.1484	.6453	.2063
GOMPERTZ	Initial	.3333	.3333	.3333
	Iteration 1	.1499	.6540	.1961
	Iteration 2	.1382	.6489	.2128
	Iteration 3	.1382	.6489	.2128
LINEAR	Initial	.3333	.3333	.3333
	Iteration 1	.1667	.6666	.1667
	Iteration 2	.1665	.6672	.1663
EXPONENTIAL	Initial	.3333	.3333	.3333
	Iteration 1	.1632	.6659	.1710
	Iteration 2	.1598	.6659	.1743
	Iteration 3	.1632	.6659	.1710
	Iteration 4	.1632	.6659	.1710

PROCOST Iteration Weights

CURVE	ITERATION	K1	K2	K3
HYPERBOLIC TANGENT	Initial	.3333	.3333	.3333
	Iteration 1	.1565	.6385	.2050
	Iteration 2	.1490	.6310	.2200
	Iteration 3	.1490	.6310	.2200
PEARL	Initial	.3333	.3333	.3333
	Iteration 1	.1301	.5729	.2004
	Iteration 2	.1440	.6342	.2218
GOMPERTZ	Initial	.3333	.3333	.3333
	Iteration 1	.1478	.6363	.2159
	Iteration 2	.1421	.6304	.2275
	Iteration 3	.1421	.6304	.2275
LINEAR	Initial	.3333	.3333	.3333
	Iteration 1	.1604	.6512	.1884
	Iteration 2	.1536	.6569	.1896
	Iteration 3	.1536	.6569	.1896
EXPONENTIAL	Initial	.3333	.3333	.3333
	Iteration 1	.1553	.6473	.1974
	Iteration 2	.1580	.6492	.1928
	Iteration 3	.1580	.6492	.1928

TDEVCOST Iteration Weights

CURVE	ITERATION	K1	K2	K3
HYPERBOLIC TANGENT	Initial	.3333	.3333	.3333
	Iteration 1	.1242	.5618	.3140
	Iteration 2	.1229	.5645	.3126
	Iteration 3	.1229	.5645	.3126
PEARL	Initial	.3333	.3333	.3333
	Iteration 1	.1250	.5599	.3151
	Iteration 2	.1225	.5655	.3120
	Iteration 3	.1225	.5655	.3120
GOMPERTZ	Initial	.3333	.3333	.3333
	Iteration 1	.1234	.5680	.3086
	Iteration 2	.1223	.5722	.3055
	Iteration 3	.1223	5722	.3055
LINEAR	Initial	.3333	.3333	.3333
	Iteration 1	.1264	.5583	.3153
	Iteration 2	.1266	.5580	.3154
EXPONENTIAL	Initial	.3333	.3333	.3333
	Iteration 1	.1255	.5606	.3139
	Iteration 2	.1255	.5600	.3145

Appendix C: Shape Parameters Range Values

CURVE	A LOW	A HIGH	B LOW	B HIGH
HYPERBOLIC TANGENT	44	104	118	178
PEARL	.0001	.01	1	5
GOMPERTZ	.0001	.02	.0001	3
EXPONENTIAL	.0005	.003	1	2

Bibliography

1. Alexander, A.J., and J.R. Nelson. Measuring Technological Change: Aircraft Turbine Engines. Rand Corporation, Santa Monica CA, R-1017-ARPA/PR, May 1972.

2. Birkler, J.L. et al. Development and Production Cost Estimating Relationships for Aircraft Turbine Engines. Rand Note. The Rand Corporation, Santa Monica CA, October 1982.

3. Crouch, James. Personal Interview. ASD/YZ, Wright-Patterson Air Force Base OH, 21 August 1984.

4. Edwards, K.L. and T.J. Gordon. "Further Research into a Convention for Measuring the State-of the Art of Products and Processes," Technological Forecasting and Social Change, 24: 153-175 (1983).

5. Engine Handbook. HQ AFLC/LOE, Wright-Patterson Air Force Base OH, October 1982.

6. Falkenstein, W.A, "Methodologies for Predicting Avionic System Capability and Weight in CTOL and VTOL Fighter/ Attack Aircraft 1975 to 1995." Paper presented at the 33rd Annual Conference of the Society of Allied Weight Engineers, Inc., Fort Worth TX, May 6-9, 1974.

7. Fong, F.K., et al. Space Division Unmanned Spacecraft Cost Model. Fifth Edition. Los Angeles CA: Space Division, June 1981.

8. Fox, J.R. Arming America: How the U.S. Buys Weapons. Cambridge MA: Harvard University Press, 1974.

9. Gordon, T.J., and T.R. Munson. "A Proposed Convention for Measuring the State of the Art of Products or Processes,"Technological Forecasting and Social Change, 24: 153-175 (1983).

10. Harman, A.J., assisted by Susan Henrichsen. A Methodology for Cost Factor Comparison and Prediction. The Rand Corporation, Santa Monica CA, RM-6269-ARPA, August 1970.

11. Large, J.P. Development of Parametric Cost Models for Weapon Systems. The Rand Paper Series. The Rand Corporation, Santa Monica CA, 1981.

12. Large, J.P., and Capt K.M.S. Gillespie. A Critique of Aircraft Airfram Cost Models. The Rand Corporation, Santa Monica CA, R-2194-AF, September 1977.

13. Martino, J.P. Technological Forecasting for Decision Making. New York NY: American Elsevier Publishing Company, Inc., 1972.

14. Martino, J.P. An Investigation of the Tradeoff Surface Technique for Technology Measurement. Prepared for the National Science Foundation, January 1984.

15. Martino, J.P. Personal Interviews. University of Dayton, Research Institute, Dayton OH, 9 April through 24 April 1984.

16. Nelson, J.R. Life-Cycle Analysis of Aircraft Turbine Engines. The Rand Corporation, Santa Monica CA, R-2103-AF, November 1977.

17. Nelson, J.R. Performance/Schedule/Cost Tradeoffs and Risk Analysis for the Acquisition of Aircraft Turbine Engines: Application of R-1288-PR Methodology. The Rand Corporation, Santa Monica CA, R-1781-PR, June 1975.

18. Nelson, J.R., and F.S. Timson. Relating Technology to Acquisition Costs: Aircraft Turbine Engines. The Rand Corporation, Santa Monica CA, R-1288-PR, March 1974.

19. Nie, N.H., et al. SPSS: Statistical Package for the Social Sciences. 2d ed. New York: McGraw-Hill, 1975.

20. Noah, J.W., et al. Estimating Aircraft Acquisition Costs by Parametric Methods. J. Watson Noah Assosiates, Inc., FR-103-USN, September 1973.

21. Preidis, R.J. Weapon System Costing: An Investigation into Cause-Effect Relationships. AFHRL Technical Paper 83-13, Wright-Patterson Air Force Base OH, June 1983.

22. Scherrer, Capt John D. Cost Analysis For Managers. Department of Special Management Techniques, School of Systems and Logistics, Wright-Patterson Air Force Base OH, September 1976.

23. Shishko, R. Some Acquisition Issues for Tactical Capabilities. The Rand Corporation, Santa Monica CA, June 1983.

24. Stanley, W.L., and M.D. Miller. Measuring Technological Change in Jet Fighter Aircraft. The Rand Corporation, Santa Monica CA, R-2249-AF, September 1979.

25. Stekler, H., et al. The Dynamics of Structural Changes in the Defense Industries. Institute for Defense Analysis, Arlington VA, IDA Paper P-1552, January 1981.

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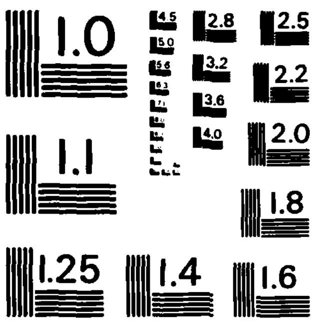

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26. Summers, Robert. Cost Estimates as Predictors of Actual Weapon Costs: A Study of Major Hardware Articles. The Rand Corporation, Santa Monica CA, RM-3061-PR, April 1962.

27. Sweeney, Lt Col K.J. The Weapon System Acquisition Process: Controlling Costs through Technology Management. USAWC Research Paper, Carlisle Barracks PA: 28 February 1973.

13. Martino, J.P. Technological Forecasting for Decision Making. New York NY: American Elsevier Publishing Company, Inc., 1972.

14. Martino, J.P. An Investigation of the Tradeoff Surface Technique for Technology Measurement. Prepared for the National Science Foundation, January 1984.

15. Martino, J.P. Personal Interviews. University of Dayton, Research Institute, Dayton OH, 9 April through 24 April 1984.

16. Nelson, J.R. Life-Cycle Analysis of Aircraft Turbine Engines. The Rand Corporation, Santa Monica CA, R-2103-AF, November 1977.

17. Nelson, J.R. Performance/Schedule/Cost Tradeoffs and Risk Analysis for the Acquisition of Aircraft Turbine Engines: Application of R-1288-PR Methodology. The Rand Corporation, Santa Monica CA, R-1781-PR, June 1975.

18. Nelson, J.R., and F.S. Timson. Relating Technology to Acquisition Costs: Aircraft Turbine Engines. The Rand Corporation, Santa Monica CA, R-1288-PR, March 1974.

19. Nie, N.H., et al. SPSS: Statistical Package for the Social Sciences. 2d ed. New York: McGraw-Hill, 1975.

20. Noah, J.W., et al. Estimating Aircraft Acquisition Costs by Parametric Methods. J. Watson Noah Assosiates, Inc., FR-103-USN, September 1973.

21. Preidis, R.J. Weapon System Costing: An Investigation into Cause-Effect Relationships. AFHRL Technical Paper 83-13, Wright-Patterson Air Force Base OH, June 1983.

22. Scherrer, Capt John D. Cost Analysis For Managers. Department of Special Management Techniques, School of Systems and Logistics, Wright-Patterson Air Force Base OH, September 1976.

23. Shishko, R. Some Acquisition Issues for Tactical Capabilities. The Rand Corporation, Santa Monica CA, June 1983.

24. Stanley, W.L., and M.D. Miller. Measuring Technological Change in Jet Fighter Aircraft. The Rand Corporation, Santa Monica CA, R-2249-AF, September 1979.

25. Stekler, H., et al. The Dynamics of Structural Changes in the Defense Industries. Institute for Defense Analysis, Arlington VA, IDA Paper P-1552, January 1981.

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